Assessment of Artificial Groundwater Recharge through the Integration of MODFLOW, Remote Sensing, GIS, and AI/ML Techniques

Synopsis of the PhD Thesis

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ABSTRACT

With the population growth, water demand rises, stressing the available water resources. Though classified as water-rich with 4% of global freshwater, India faces declining per capita water availability, largely due to groundwater over-extraction, This challenge intensifies during summer, when water scarcity affects rural communities and livestock. In Maharashtra's drought-prone districts like Aurangabad, Jalgaon, and Nandurbar, as well where the rainfall pattern or hydrogeological characteristics are varying then Groundwater Recharging (GWR)has become essential. Artificial recharge methods including Stream Augmentation, Bladder Pillow Tank, Dugwell Recharge, Induced Recharge, Pit/Shaft Recharge can effectively replenish aquifers. Understanding geology, slope, land use, and rainfall patterns is crucial. In this study, GIS and Remote Sensing tools are used to map elevation, slope, soil types, and watersheds, identifying suitable zones for recharge.

AI-ML techniques such as ARIMA, CNN, and LSTM have been applied while the FDM base MODFLOW is used for predicting groundwater levels, FDM base MODFLOW model has been used to simulate groundwater Recharging Levels and for comparative analysis of prediction accuracy.

The different predictive models are developed for checking the suitability of recharge zones and techniques. The models are validated for accuracy, precision, recall, and efficiency metrics. Groundwater level simulations before and after recharge interventions showed significant improvement. This integrated approach combining hydrological analysis, GIS-RS mapping, and ML prediction offers scalable solutions for improving groundwater sustainability. By leveraging technology and strategic planning, India can better manage its water resources in the face of increasing demand and climate uncertainty.

In this study, an overview of different methods of groundwater recharging are discussed. The optimum solutions for draught prone areas will also be explored using integrated Approach two case studies are presented to check the effectivity of the models

Keywords: *Artificial Groundwater recharge, GIS, MODFLOW, RS, AI-ML techniques*

INTRODUCTION

Although Earth appears as the "blue planet," only about 3% of its 1400 billion cubic meters (BCM) of water is fresh, and merely a fraction of that around 11% exists as extractable groundwater within 800 meters of depth. This limited resource plays a vital role in India, meeting over 85% of rural domestic needs, 50% of urban requirements, and more than half of the country's irrigation demands(Kumar 2022).

However, over-extraction has critically endangered groundwater reserves, especially in India, where erratic rainfall and increasing demand have led to steep declines in water tables. Central Ground Water Board (CGWB) assessments have already categorized several blocks as "over-exploited" or "critical," highlighting the urgent need for corrective measures. Groundwater Recharging (GWR), especially through artificial Recharging methods such as Stream Augmentation, Bladder Pillow, Pit/Shaft Recharge, Dugwell Recharge, Borwell Recharge, Induced Recharge presents a practical and globally accepted solution to mitigate this crisis.

Yet, despite decades of efforts, a significant research gap exists in the integration of spatial hydrological understanding with advanced data-driven predictive techniques. Many earlier studies have failed to incorporate modern GIS, Remote Sensing, and machine learning-based approaches that can precisely identify suitable recharge zones and guide cost-effective interventions. This study addresses that gap by combining geospatial mapping of terrain features (slope, soil type, land use, drainage) with AI-ML models like Arima, LSTM, CNN performance metrics such as accuracy and precision. The approach not only enables targeted recharge planning but also enhances prediction accuracy through model-based simulation and validation. As groundwater depletion threatens water security across drought-prone regions, such integrated frameworks are essential for sustainable water resource management and long-term ecological resilience.

2.1 Darcy's Laws

Darcy's law serves as a foundational principle in hydrogeology, providing critical insight into the flow of groundwater through porous media. This principle, established by Henri Darcy in the 19th century, is vital for understanding dynamics of groundwater movement and particularly significant in estimating GWR the process by which water infiltrates from the surface into the groundwater system(Brown and Signor 1974). Darcy's Law explains how groundwater flows in response to

differences in hydraulic head and the properties of the geological materials through which it moves. By analyzing the hydraulic gradient (the change in water pressure over a distance) and the hydraulic conductivity (which reflects the permeability of the soil or rock), the rate at which water infiltrates into aquifers can be estimated(Sun et al. 2024).

2.2 GIS and Remote sensing:

Geographic information system (GIS) approach is helpful to identify favorable regions for construction of artificial recharge structures. GIS overlay analysis can be carried out wherein few parameters like geology, geomorphology, slope, soil, land use, weathering depth and waterbodies/drainage are integrated. Survey of India topo sheet, Indian Remote Sensing Satellite data and ASTER DEM data is useful to develop the various thematic maps. These maps are later transferred to raster data. Four zone namely very high, high, moderate and very poor have been demarcated. About 45% of the study area is categorized as high to very highly feasible zone. The existing artificial recharge structures in the region can be plotted and proposed artificial recharge structures can be identified. (Shekar and Mathew 2024).

Studies related to groundwater potential mapping with various data models have become increasingly common. Numerous factors that affect groundwater potential have been proposed based on various data modeling, including statistical models, probabilistic models, machine learning models, and data mining models; yield and spring or well location data are also widely used as groundwater potential indicators (Fernandes et al. 2024).

The aim of the study is to demarcate the Groundwater Recharge zones for better management of the aquifer system in the regions where the dependency on groundwater has significantly increased in recent years. This relentless groundwater withdrawal for various sectors (irrigation, domestic and industries) caused the lowering of groundwater levels, long-term declining trend and even drying up of wells. Various measures such as rainwater harvesting, artificial recharge and water use efficiency are successfully practiced by Central and State agencies. But for effective implementation of artificial recharge schemes, identification of appropriate location and structure is crucial. Several scientists have applied integrated GIS & RS techniques to identify potential groundwater zones. Researchers have used the geospatial expertise for groundwater studies by interpreting thematic layers such as geomorphology, geology, drainage pattern, lineament, soil, rainfall intensity slope etc.

Fig.1 provides a summary of artificial groundwater recharge (GWR) techniques and their classification into surface, sub-surface, and combination methods.

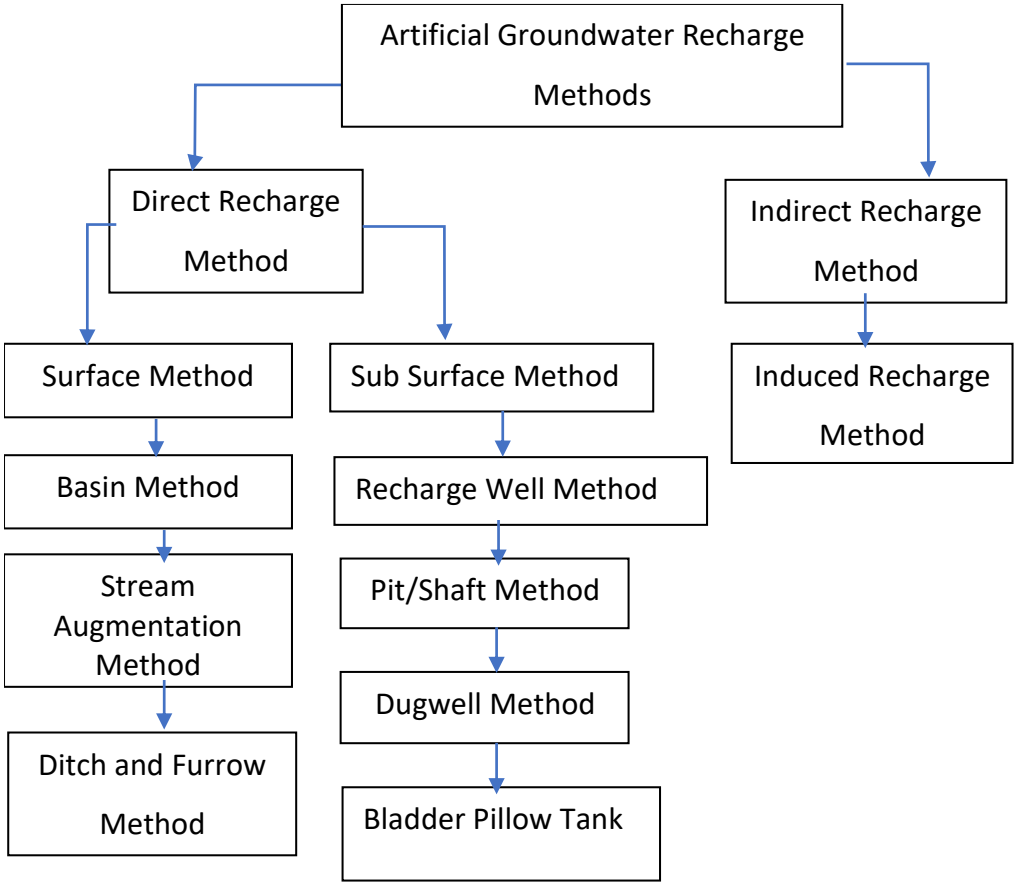

Fig No:1 Summary of artificial GWR techniques and types

2.3 Image Classification for RS: RS Classification involves labeling the pixels as belonging to a particular spectral and thus information classes using the spectral data available. The image classification procedure is to automatically categorize all pixels in an image into land cover classes or themes. Image classifiers are used in hybrid mode and the approach depends upon the nature of the data being analyzed, the computational resources available, and the intended application of the classified data.

The Three most common remote sensing classification methods are:

1.Unsupervised classification
2.Supervised classification
3.Object-based image analysis

2.3.1 Unsupervised Classification: Unsupervised classification is a process where software automatically groups pixels with similar characteristics in an image without user-defined sample classes. The user can choose the algorithm and number of classes, but the classification is done by the software. However, the user must understand the area to accurately relate the grouped pixels to real-world features like wetlands or forests(Xu et al. 2024).

2.3.2 Supervised Classification: In supervised classification, the analyst guides the process by providing known sample areas (training sites) for each land cover type. These samples help the software create a reference of spectral characteristics for each class. The software then compares all image pixels to this reference and assigns them to the closest matching class. In this method, the user defines the information categories first and checks if they are spectrally distinct. Since it uses known data, supervised classification usually produces more accurate results than unsupervised classification.

2.3.3 Object-based image analysis: Image stacking in IMAGINE is not a built-in function but a visualization technique that uses several available tools. First, the original image is opened in the Viewer. Then, using the "Open Raster Layer" option from the File menu, the classified image and its signature files are added. By selecting "fit to window" and deselecting "replace image," the classified image is layered on top of the original. To view each classification separately, the opacity of all other signatures is set to zero. This allows each class to be viewed over the original image, effectively stacking them to form a fully classified image(Kucharczyk et al. 2020).

2.4 Machine Learning Techniques:

Machine learning (ML) is a branch of artificial intelligence that enables systems to learn patterns from data and make predictions without being explicitly programmed. In the context of groundwater level (GWL) prediction, ML techniques help model complex, non-linear relationships between various hydro-meteorological parameters. Methods like LSTM are used

for capturing long-term temporal trends, while CNNs extract spatial patterns from gridded data. Traditional models like ARIMA are still valuable for linear time-series forecasting. Other effective methods include Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (XGBoost), Artificial Neural Networks (ANNs), and Autoencoders, each offering unique advantages depending on data characteristics and prediction goals.

2.4.1 Long Short-Term Memory (LSTM): is a type of deep learning model designed to handle sequential data like time series. It can remember patterns over long periods, making it useful for predicting values such as groundwater levels or rainfall.

2.4.2 AutoRegressive Integrated Moving Average (ARIMA): is a statistical method used for forecasting time series data, especially when the data is linear and follows a consistent trend. It combines past values and past errors to make predictions.

2.4.3 Convolutional Neural Network (CNN): is mainly used for analyzing images, but it can also be applied to time series or spatial data. It works by automatically detecting important features or patterns in the data, making it useful for tasks like satellite image analysis or detecting changes in land use.

2.5 Empirical Methods

Empirical relationships between GWR and rainfall are often established through seasonal groundwater balance studies. By analyzing data such as precipitation, evapotranspiration, and changes in groundwater levels across different seasons, recharge rates can be identified linking with rainfall amounts. These studies help to better understand how variations in rainfall contribute to groundwater replenishment, providing a foundation for predicting GWR under different climatic and hydrological conditions.

Such an approach enables the development of predictive models that estimate GWR based on seasonal rainfall variability. These models are particularly valuable for water resource management, as they can guide decision-making in regions where rainfall patterns directly influence aquifer sustainability. For example, (Islam et al. 2015)explored the relationship between rainfall and recharge using empirical methods, highlighting how recharge rates vary with seasonal precipitation changes in different hydrogeological settings.

Establishing empirical relationships between rainfall and recharge is critical in regions affected by climate variability or water scarcity. By identifying and quantifying these relationships, water managers can

- Predict the impacts of drought or changing rainfall patterns on groundwater resources.
- Design effective groundwater management and recharge enhancement strategies.
- Support sustainable groundwater extraction practices in agricultural, urban, and industrial sectors.

Closure: The different tools used for assessing groundwater potential, including GIS, RS, and various AI/ML techniques, are discussed

OBJECTIVES

- To identify and delineate groundwater potential zones with the integration of various thematic maps using GIS techniques
- To study challenges regarding meteorological parameters and geological conditions in groundwater recharging
- To implement artificial groundwater recharge system using supervised and unsupervised image classification

LITERATURE REVIEW

Groundwater is a huge reserve of water underneath the Earth's surface vital for humans and ecosystems. Approximately a third of the water used originates from underground sources(Cui et al. 2018). and nearly 2 billion people globally utilize groundwater for drinking purposes (Huan et al. 2018). In regions lacking sufficient surface water supply from rivers and reservoirs, groundwater is critical for meeting the water demand. The demand for groundwater is rapidly increasing with the rise in population. Furthermore, climate change is imposing additional stress on surface and groundwater sources. Therefore, it is essential to understand climate change impacts on groundwater resources to achieve sustainable water resource management (Pltonykova et al. 2020).

The literature review is structured into three main parts: (1) methods of groundwater recharge, (2)Artificial Groundwater Recharge (3) the application of GIS and remote sensing in groundwater recharge assessment, and (4) the use of artificial intelligence and machine learning techniques in evaluating and enhancing groundwater recharge.

4.1 Methods of groundwater recharge

Groundwater is the water stored beneath the Earth's surface in soil and rock layers, essential for drinking, irrigation, and industry. Recharge techniques help replenish it, with methods like stream augmentation, which increases Surface & Stream flow to boost infiltration, and bladder tanks, which store water temporarily for controlled recharge. Surface methods like check dams and percolation tanks allow water to seep into the ground, while subsurface methods such as recharge wells and injection wells direct water below ground. These approaches are chosen based on land, soil, and water conditions to ensure effective groundwater restoration(Adhikari et al. 2022).

Groundwater recharge is highly beneficial for the public as it helps maintain water availability during dry periods, supports agriculture, and reduces the risk of water scarcity(Chin and Lee 2008).It improves the reliability of wells and borewells, especially in rural areas, and helps control land subsidence. Recharge techniques also reduce surface runoff, lowering the risk of floods and enhancing overall water security for communities(Patel and Chaudhari 2023). Climate change influences groundwater systems in several ways. The most direct climate change effect on groundwater is related to the GWR as climate change can alter rainfall amounts and patterns, thus

changing the quantities of soil infiltration, deep percolation, and hence the recharge. Moreover, a rise in temperature increases the rate of evaporation, reducing the quantity of water available to replenish groundwater. In addition to GWR effects, climate change has significant influences on groundwater quality. Climate change has an influence on groundwater quality through changes in physical, chemical, and biological properties of the aquifer in both drier and wetter scenarios, as these properties are highly related to climatic factors. Under drier conditions, an increase in total dissolved solids through an increase in salt content will cause groundwater quality degradation(Al Atawneh et al. 2021). Techniques like percolation tanks and check dams (dams on small gully) enhance GWR and improve water quality, particularly in semi-arid regions(Bhattacharya 2010). Groundwater conservation is essential for both the environment and society due to its far-reaching impacts on sustainable water supply, agricultural support, ecosystem conservation, and drought resilience. Additionally, it plays a critical role in preventing land subsidence, protecting water quality, adapting to climate change, preserving cultural and social values, and enhancing GWR. As a vital resource, groundwater supports numerous livelihoods, ecosystems, and communities, making its conservation a top priority in water resource management. One of the most effective strategies for groundwater conservation is GWR(Kebede et al. 2024). which involves replenishing aquifers to maintain their sustainability and functionality This can occur naturally, through precipitation and infiltration, or artificially, by directing water into aquifer systems through recharge structures (Abraham and Mohan 2015). Natural Groundwater Recharge (GWR)

Natural GWR is a process through which water from precipitation and other surface sources infiltrates the ground, replenishing underground aquifers (Hashemi et al. 2013). This occurs when rainwater or melted snow seeps into the soil and permeable rock layers, gradually making its way to the groundwater table. The efficiency and rate of natural recharge are influenced by a variety of factors, including soil type, geology, land cover, topography, depth to groundwater table, vegetation and climate conditions. Favorable conditions for natural recharge include permeable soils, fractured rock formations, perennial rivers and streams, forest cover, and relatively level land with minimal slope, all of which enhance the infiltration of water into the subsurface.(Barthel et al. 2021)

However, natural GWR can be significantly reduced or obstructed due to a variety of factors, many of which are driven by human activities and environmental changes. Urbanization is one of the

main contributors to reduced recharge, as the expansion of impervious surfaces such as roads, pavements, and buildings prevent water from infiltrating into the soil. Instead, water flows off these surfaces into storm drains, reducing the amount of water available for aquifer replenishment(Patel and Chaudhari 2023).

In addition, excessive groundwater extraction can outpace natural recharge rates, leading to a decline in the water table. Over-extraction can also reduce the effectiveness of recharge, as deeper groundwater levels make it harder for infiltrating water to reach aquifers. Climate change further exacerbates these challenges by altering precipitation patterns and intensities. For instance, an increase in the frequency and intensity of droughts, along with shifts in rainfall distribution, can reduce the overall availability of water for recharge. Areas that experience heavy rainfall over short periods may see more surface runoff than infiltration, further limiting the water that reaches the aquifer. Another critical factor affecting natural recharge is the discharge of polluted water into natural waterways. Polluted water can block soil pores with impurities, reducing the soil's infiltration capacity. Industrial discharges, untreated wastewater, and contaminated surface water flows prevent water from percolating effectively into the ground, thereby hindering natural recharge processes(Raimondi et al. 2023).

4.2 Artificial Groundwater Recharge (GWR)

Artificial GWR is a method of replenishing groundwater reservoirs by deliberately modifying the natural movement of surface water, treated wastewater, rainwater, etc., using appropriate civil/hydraulic engineering techniques (Gontia and Patil 2012). This process is typically implemented in situations where natural recharge is insufficient to meet groundwater demand throughout the year and store water for later use. By employing artificial recharge, water managers can enhance the sustainability of aquifers and ensure the availability of groundwater for various uses. The primary objectives of artificial recharge techniques are to. (1) enhance natural recharge: replenishing aquifers by capturing and directing precipitation and surface runoff into the ground; (2) stabilize aquifer levels: contributing to maintaining consistent groundwater levels; (3) control contamination of water supplies: protect groundwater quality and reduce the risk of pollutants infiltrating aquifers (recharged water quality is controlled); and (4) prevent freshwater degradation: minimize salt water intrusion in coastal areas (Abu-Taleb 2003). These techniques are especially valuable in areas with high water demand, limited natural recharge, or increasing pressure on

groundwater resources due to climate change, urbanization, and population growth. Groundwater levels can be improved through various artificial recharge methods, including spreading, recharge/injection wells, and the induced infiltration method (Li et al. 2021)

According to Mukherjee (Mukherjee 2016), the first two methods—spreading and recharge/injection wells—are classified as direct techniques, with spreading involving the application of water directly to the surface, while recharge/injection wells operate below the surface. In contrast, the induced infiltration method falls under the indirect category, as it utilizes the natural processes of infiltration from nearby water sources to enhance GWR. Examples of induced infiltration method include induced recharge, aquifer modification, and groundwater conservation structures (Bhattacharya 2010). Zhang et al. (Zhang et al. 2020)presented an in-depth review and analysis on historical development, the current situation, and perspectives of managed aquifer recharge.

established a density-dependent groundwater flow model to examine the effect of seawater intrusion in the coastal aquifer system of the Netherlands. Similarly, the numerical model (MOCDENS3D) study helped to calculate the fluctuations in coastal groundwater flow .Numerical models have been used by several researchers to estimate the regional groundwater budget in different aquifer systems , to predict the consequences of proposed development actions, to link any connection between locations and aquifer boundaries, and to assess the groundwater quality within the aquifer system and the amount of natural recharge to a particular aquifer (Kashaigili et al. 2003). A visual MODFLOW software package has been used worldwide for groundwater flow simulation as it is user-friendly and robust.

Although substantial research on GWR and water harvesting (WH) techniques has been conducted between 2000 and 2024, several critical gaps remain. Traditional methods such as Darcy's Law, empirical rainfall-recharge relationships, and numerical models like MODFLOW are widely applied; however, there is limited integration of emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and remote sensing for real-time forecasting and spatial trend analysis of groundwater systems. Innovative local solutions such as steam augmentation bladder pillows used in Aurangabad have received little scientific evaluation, despite their potential to enhance recharge. Moreover, existing models often rely on static or point-based data, lacking dynamic spatio-temporal analysis using RS-GIS tools. The coupling between surface water

harvesting structures and their measurable impact on subsurface recharge is also underexplored, particularly regarding runoff-infiltration interactions. Many global models are not calibrated to local geological and hydrological conditions, especially in regions like Maharashtra with basaltic terrain, indicating a need for region-specific calibration and validation. Lastly, GWR studies often overlook socio-economic and policy dimensions, with minimal integration of hydrogeological findings into decision-support systems for sustainable water resource management.

4.3 The application of GIS and RS in groundwater recharge assessment

The application of GIS and RS has significantly enhanced groundwater recharge assessment by providing accurate, spatially distributed information over large areas (Tao et al. 2022). These tools are widely used to identify suitable zones for artificial recharge by analyzing key factors such as soil texture, land use/land cover, slope, geology, drainage patterns, and rainfall distribution (Babiker et al. 2007).Remote sensing provides up-to-date satellite imagery that helps in monitoring land surface changes, while GIS integrates and analyzes multiple thematic layers to prioritize potential recharge sites (Maghribi and Supriatna 2020). This approach not only saves time and resources compared to traditional field methods but also supports better planning and decision-making. By combining GIS and RS, researchers and planners can develop detailed recharge maps, optimize site selection, and design efficient recharge structures, ultimately contributing to the sustainable management of groundwater resources(Wang et al. 2024).

4.4 The use of AI and ML techniques in evaluating and enhancing GWR.

The use of AI and ML techniques in evaluating and enhancing GWR has become increasingly important in recent years. These advanced computational methods can analyze complex, non-linear relationships between various hydrological, meteorological, and geological parameters that influence groundwater recharge. Models such as ANN, SVM, Decision Trees, and LSTM networks are widely used to predict groundwater levels, identify recharge potential zones, and assess the impact of recharge interventions (Rakovec et al. 2022). AI and ML techniques help improve the accuracy of predictions, reduce the need for extensive field data, and enable continuous learning from new datasets (Aalbers et al. 2023) By integrating AI/ML with GIS and remote sensing data, researchers can develop intelligent decision-support systems that enhance the planning and management of artificial recharge methods, contributing to more sustainable groundwater use(van den Eertwegh et al. 2021).

Closure: The integration of MODFLOW, remote sensing, GIS, and machine learning has significantly advanced GWR studies. MODFLOW provides precise simulation, while RS-GIS offers spatial insights, and ML enhances prediction by uncovering complex patterns. Together, they enable accurate assessment and optimization of recharge strategies

Methodology

Step 1: Population and Groundwater Demand Estimation

- Collect present population data and project it.
- groundwater demand (domestic, agricultural, industrial) using: Per capita water demand (litres/day). Projected per capita water and Gw demand
- Calculate total annual groundwater demand m^3/day.

Sources census of India CGWB well data ,

Step 2: Inventory of Groundwater Sources

- Collect historical groundwater data from CGWB monitoring wells.
- Data existing sources: open wells, borewells, handpumps, etc.
- Determine the Gap between demand and availability of Gw
- Sources: Central Ground Water Board reports and Minor Irrigation Census data.

Step 3: Data Collection (Spatial, Climatic, Hydrogeological)

- Satellite imagery (e.g., Landsat, Sentinel) for LULC and NDVI.
- DEM (30m or higher resolution) from SRTM or ASTER for terrain analysis.
- Climatic inputs: Rainfall (NASA Power Last 30 years), temperature, infiltration rate, SMD, and base flow.
- Hydrogeological maps for aquifer thickness, permeability, storativity, porosity.
- River basin and watershed data from India-
- Sources: WRIS, Bhuvan, or NRSC and NASA Power.

Step 4: Generation of GIS-Based Thematic Layers for Terrain and Watershed Analysis

Satellite imagery (e.g., Landsat, Sentinel) for LULC and NDVI.

- Slope, elevation, and drainage using DEM
- LULC and vegetation cover
- Contour lines, gradient direction, and slope face shading
- Identified Potential Zones For Artificial Rechanging

Step 5: Artificial Recharge Planning

- Identification of potential artificial recharge based on map/ data available
- Propose suitable artificial recharge Techniques: Pond, shaft, Percolation Tank, Bladder Pillow, Stream, Pits. Induced Ponds, Dugwell, Bore wells
- Evaluate suitability based on topography, soil infiltration, and LULC.

Step 6: Groundwater Flow Simulation

- Simulation and Predication of groundwater flow using MODFLOW software.

Step 7: AI/ML-Based Prediction

- Selection of al ml techniques for Gw level forecasting
- ARIMA, LSTM, and CNN were chosen for groundwater level forecasting due to their effectiveness with temporal and spatial hydrological data.
- ARIMA captures linear trends with low computational demand, while LSTM handles non-linear, long-term dependencies.
- CNN extracts spatial patterns from DEM, LULC, and rainfall data.
- Comparison of AI-ML techniques wrt simplicity, accuracy, and low data availability
- Comparison with Modflow

Perform trend analysis on rainfall, groundwater levels, and infiltration using:

- Time Series models (ARIMA, LSTM, CNN) Compare with Modflow
- Train models using historical data (1990–2023) and forecast till 2030.

Predict:

- Future groundwater levels

Step 8: Validation and Model Accuracy

Validate simulation and prediction results using Historical groundwater data.

Performance metrics:

- R^2 (coefficient of determination)
- RMSE (Root Mean Square Error)
- NSE (Nash-Sutcliffe Efficiency)

Cases Studies:

1 Stream Augmentation and Bladder Pillow tank for Aurangabad,

2.Trend analysis for Himachal Pradesh

CONTRIBUTION

Objective 1: To identify and delineate groundwater potential zones with the integration of various thematic maps using GIS techniques

In this study, the integration of various thematic layers using GIS and RS techniques enabled the precise delineation of groundwater (GW) potential zones in the Aurangabad district. Key layers such as elevation, slope, soil type, Land Use/Land Cover (LULC), hill shade, stream network, and watershed boundaries were generated and analyzed using RS data. Each map provided critical insights into surface and subsurface conditions influencing groundwater infiltration and storage.

A multi-criteria evaluation (MCE) approach is adopted where each layer was weighted based on its hydrogeological significance. For instance:

- Low slope (<5%) areas were prioritized due to their favorable infiltration potential.
- Alluvial and weathered basalt zones with higher permeability were highlighted for recharge interventions.
- Vegetated zones and agricultural land were identified as more suitable for recharge compared to built-up areas.

The composite overlay of these layers allowed the identification of 37 suitable locations across various talukas for implementing artificial recharge structures. The GIS-based delineation method significantly reduced uncertainty in site selection and provided a spatially accurate and scalable solution for regional water management.

Objective 2: To understand the meteorological and geological conditions influencing groundwater recharge and assess its applicability, a case study has been Studied in Aurangabad, Maharashtra.

Aurangabad, situated in the north-central part of Maharashtra, India, is a city steeped in history and culture. Covering an expanse of 10,107 km^2, the district is positioned between latitudes 19° 150 and 20° 400 north and longitudes 74° 370 and 75° 520 east. Surrounded by districts such as Jalgaon to the north, Nashik to the west, Ahmednagar, and Beed to the south, and Parbhani and Buldhana to the east, Aurangabad is not only a city but also a gateway to numerous ancient wonders. The district boasts several captivating landmarks, including the architectural marvel

Bibi-ka Maqbara, the historic Panchakki, and the UNESCO World Heritage Sites, Ajanta, and Ellora Caves. These sites attract tourists from around the globe, showcasing the rich cultural heritage of India. Aurangabad district comprises nine smaller districts (Talukas) – Aurangabad, Kannad, Soygaon, Sillod, Phulambri, Khuldabad, Vaijapur, Gangapur, and Paithan – ensuring efficient administration. With a total area of 10,100 km^2, of which 726 km^2 are covered by forests, the district's landscape is diverse and picturesque. Agriculture is the backbone of the region, with approximately 60% of the population relying on GW for sustenance. Notably, the district is home to the renowned Ellora and Ajanta caves, adding historical significance to its natural beauty. The Daulatabad fort and Bibi-ka Maqbara structures stand as testaments to the region's historical prominence. In essence, Aurangabad stands as a harmonious blend of cultural heritage, historical treasures, and natural splendour, making it a captivating destination for both residents and visitors seeking a journey through time and culture. The location map (Fig. 2) shows Aurangabad's geographical setting, while the elevation map (Fig. 3) highlights terrain variations affecting groundwater flow and recharge.

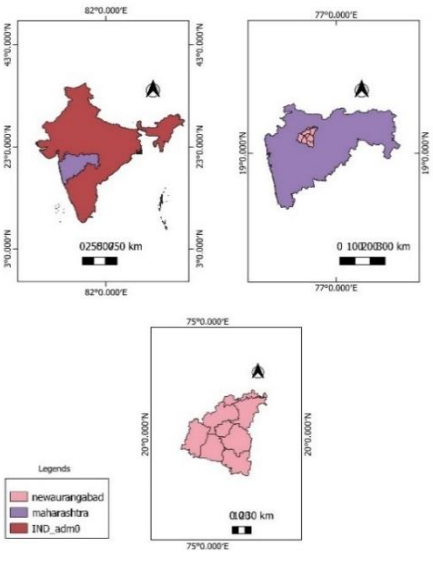

Fig 2: Location Map

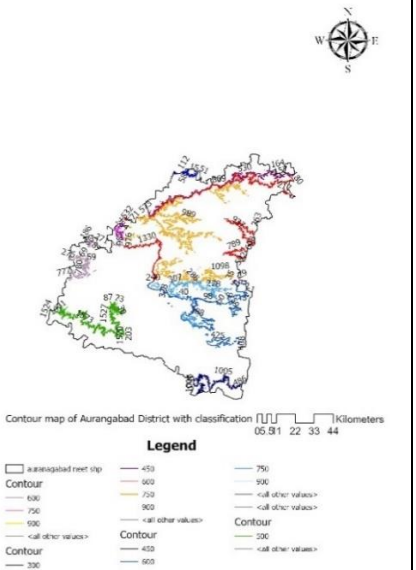

Fig 3: Elevation Map

The pre-monsoon depth to water level in Aurangabad district, observed in May 2011, reveals a predominant depth of 5-10 m below sea level (mbgl) across most of the region. However, in the

Sillod and Soygaon talukas in the northeastern section, depths between 2-5 mbgl are noted. Notably, Vaijapur, Gangapur, Khuldabad, and Chauka talukas exhibit deeper levels, ranging from 10 to 20 mbgl. The November 2011 map indicates depths ranging from 0 to 5 meters below ground level (mbgl) in the district's northern, central, and southern regions The eastern and western regions show depths of 5-10 m below the surface, while the eastern region of Aurangabad Taluka notes depths between 10 and 20 mbgl.

Analyzing water level trends from 2002 to 2011 for 43 monitoring stations, an increase is observed during the pre-monsoon period at 26 stations, ranging from 0.06 to 1.30 meters per year. Two stations show decreasing trends, ranging from 0.04 to 0.08 meters per year. Post-monsoon, water levels rise at 16 stations, varying from 0.04 to 1.26 meters per year, with a difference of 15 stations showing a decline. The overall trend indicates rising water levels in most of the district at a rate of 0 to 0.20 m per year.

Fig 4 and Fig 5 depict the aquifer depths during pre-monsoon and post-monsoon periods, respectively.

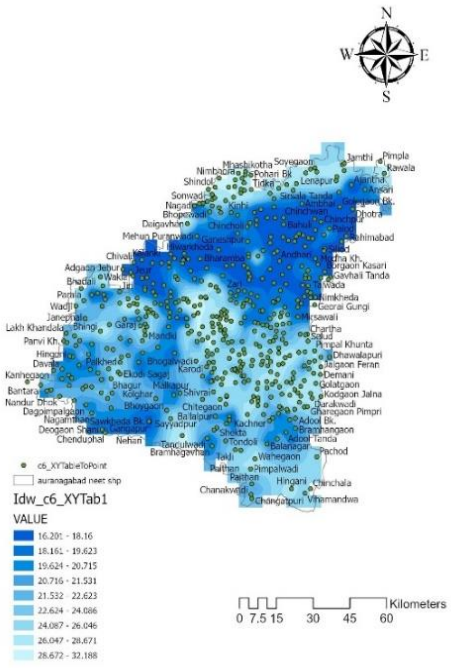

Fig. 4: Aquifer Depth level Pre-monsoon in mbgl of Aurangabad

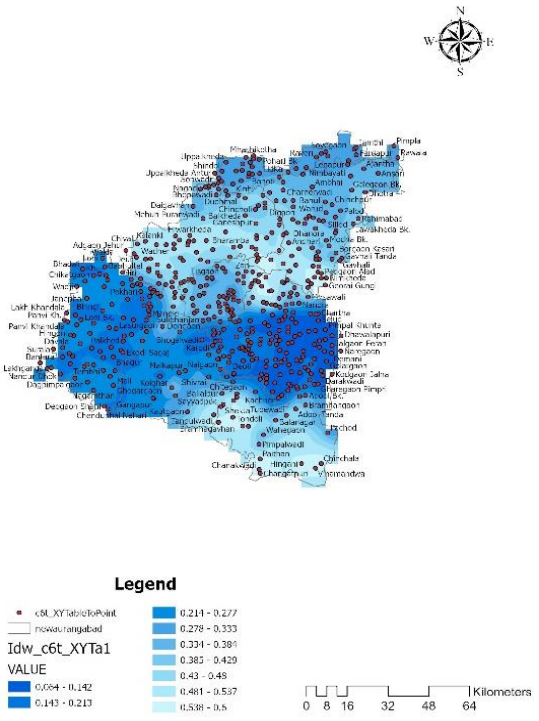

Fig.5: Aquifer Depth level post-monsoon in mbgl of Aurangabad

Dugwells, especially in basaltic terrain, show varying depths and yields, with those in morphological depressions producing more water. Borewells in Deccan Trap Basalt exhibit fluctuations in discharge, ranging from 500 to 3000 Liters per hour. Fig. 6-Fig. 11 illustrate these hydrogeological conditions of Aurangabad district.

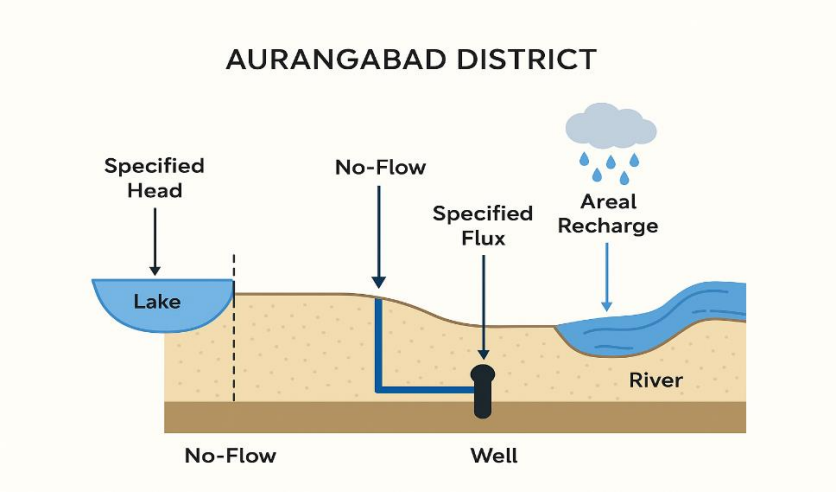

Fig 6: Boundary condition incorporated

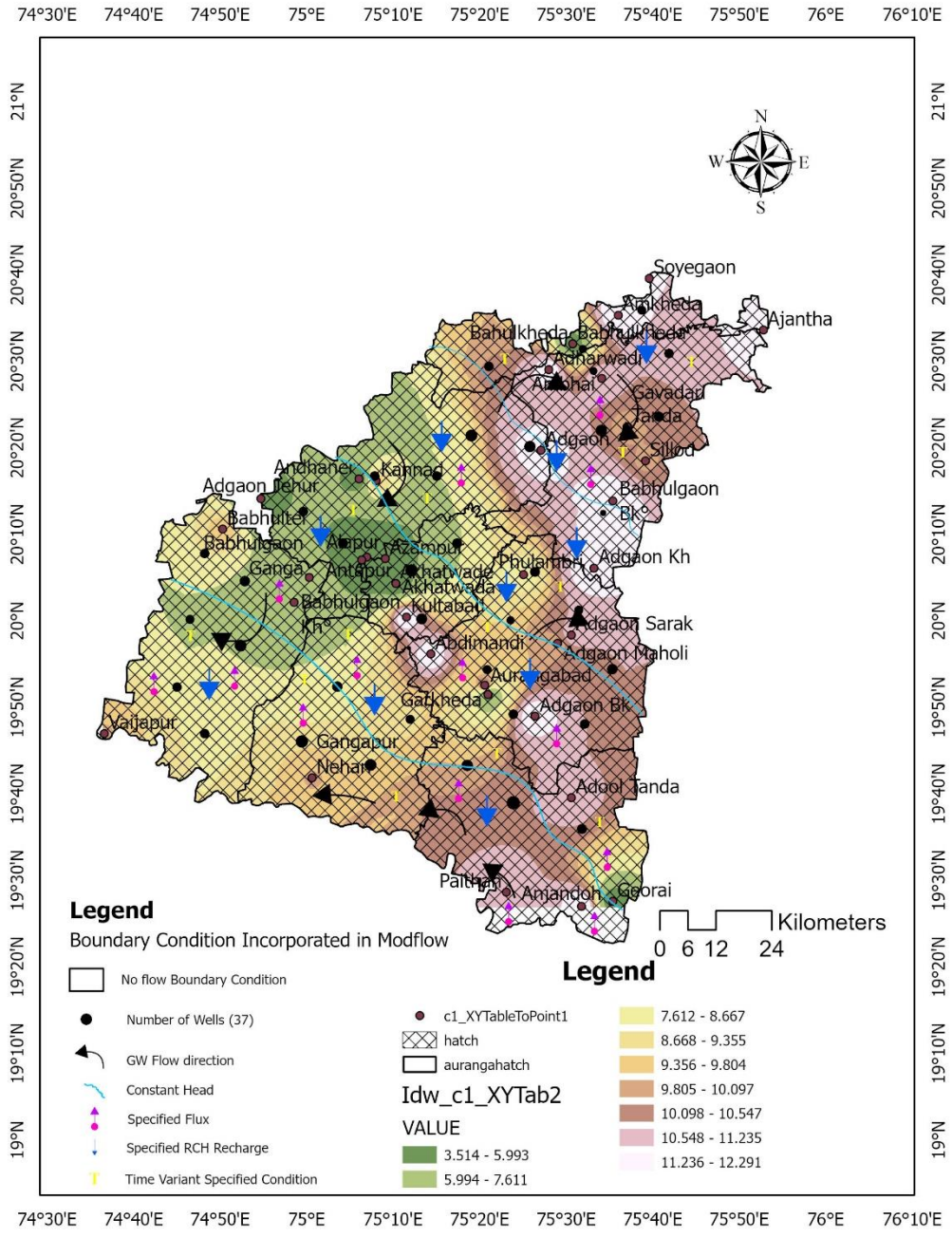

Fig.7: Aquifer Boundary Condition incorporated In Modflow

The above Fig.7 illustrates the conceptual groundwater model of Aurangabad District using the district shapefile as the base map. The northern boundary is represented as a Constant Head (CHD) Package condition, simulating a fixed groundwater level that may correspond to perennial surface water sources or regional water table control. The western edge is modelled

as a No-Flow Boundary (IBOUND=0), representing the natural watershed divide where groundwater flow does not cross. Recharge (RCH) Package is applied uniformly across the district to simulate rainfall infiltration, a key source of groundwater replenishment during the monsoon season. Time-Variant Specified Conditions are applied along the southeastern part of the district, representing seasonal fluctuations in river stage and groundwater levels. A network of 37 distributed wells (WEL) is incorporated across the district to simulate pumping and extraction, which helps in understanding drawdown patterns and aquifer response. This schematic provides a realistic representation of the hydrogeological system and is ideal for running groundwater flow simulations in MODFLOW.

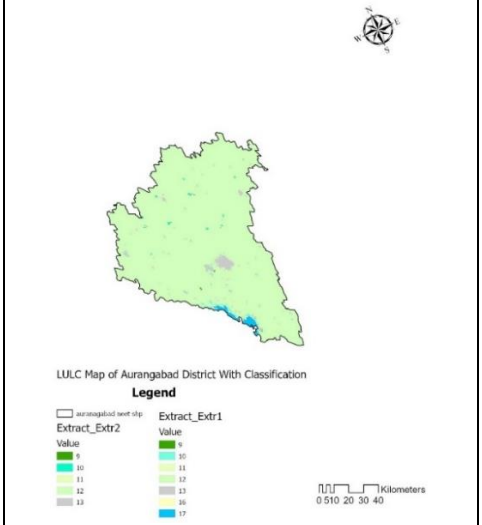

Fig. 8: LULC map of Aurangabad

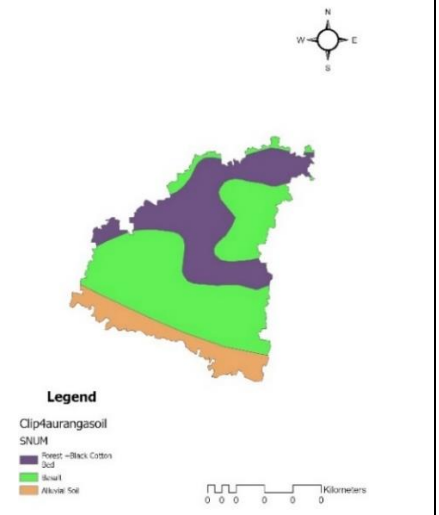

Fig. 9: Soil Map of Aurangabad

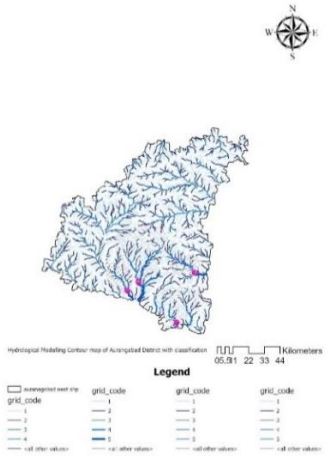	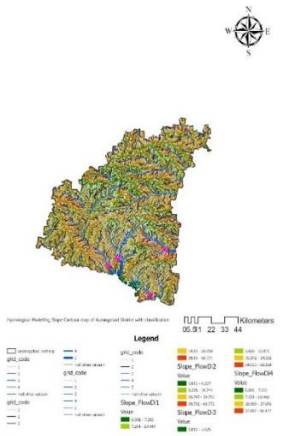
Fig. 10: Stream with hill shade map of Aurangabad	Fig.11: Slope map with Hydrological modelling of Aurangabad

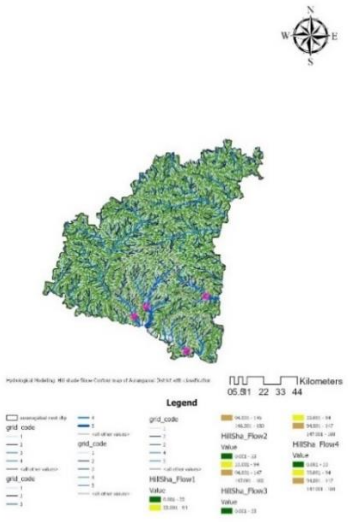	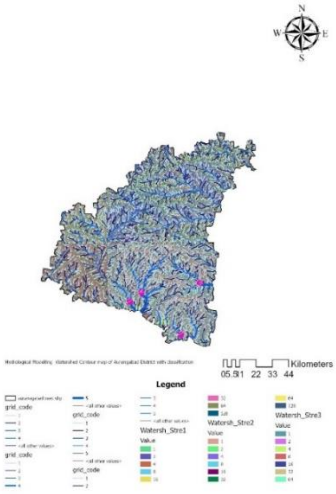
Fig. 12 : Hill shade Map of Aurangabad	Fig. 13: Watershed Map of Aurangabad

Fig 12: Hill shading illustrates the visualize elevation, slopes, and catchment areas, which are vital for identifying natural recharge zones in drought-prone regions. By clearly showing ridges, valleys, and gentle slopes, it guides the placement of check dams, percolation tanks, and recharge structures to maximize groundwater infiltration. In drought studies, hill shaded maps help locate areas where runoff can be captured and stored, reducing vulnerability during dry periods and improving long-term water security.

Groundwater Demand

The projected population for Aurangabad District is calculated and is shown in Table 1.

Table 1: GW demand for the projected population of Aurangabad (sources: https://www.census2011.co.in/census/district/353-aurangabad.html)

Year	Population	GW Demand in MCM	Difference
2021	45,70,000	738.93 MCM	56.59 MCM
2026	49,20,000	795.52 MCM	
2031	50,80,000	821.39MCM	25.87 MCM

After considering all the parameters and rainfall data From Nasa Power (https://power.larc.nasa.gov/data-access-viewer/), it is required to select the appropriate aquifer recharging technique for Aurangabad district. Fig. 14 gives the flowchart for the selection of aquifer recharging.

Groundwater is frequently over extracted in drought-prone areas in Aurangabad district in way to order to supply residents, businesses, and agriculture with the water they need. Refer Fig 15-17. This causes groundwater levels to drop, and in extreme situations, it can cause aquifers to run dry. For this area stream augmentation technique can be useful. The decision for the selection of this technique is explained in the Fig. 14.

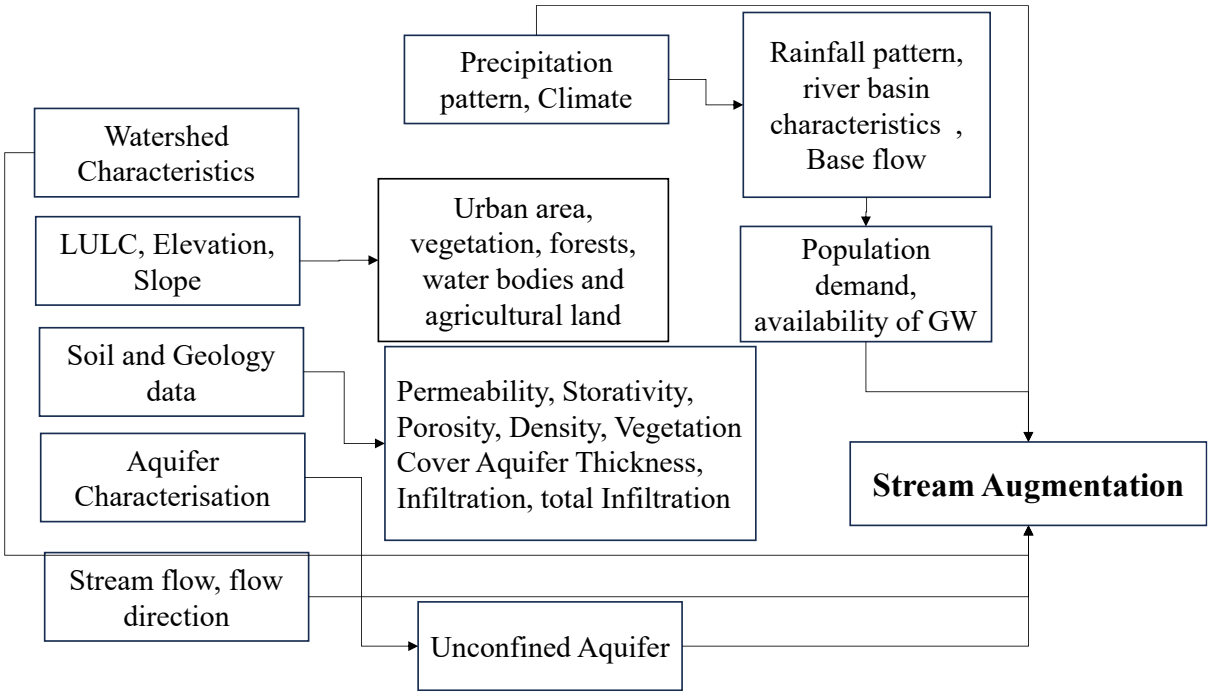
Precipitation pattern, Climate
Rainfall pattern, river basin characteristics , Base flow
Watershed Characteristics
LULC, Elevation, Slope
Urban area, vegetation, forests, water bodies and agricultural land
Population demand, availability of GW
Soil and Geology data
Permeability, Storativity, Porosity, Density, Vegetation Cover Aquifer Thickness, Infiltration, total Infiltration
Aquifer Characterisation
Stream Augmentation
Stream flow, flow direction
Unconfined Aquifer

Fig. 14: Flow chart for the selection of aquifer recharging technique for Aurangabad.

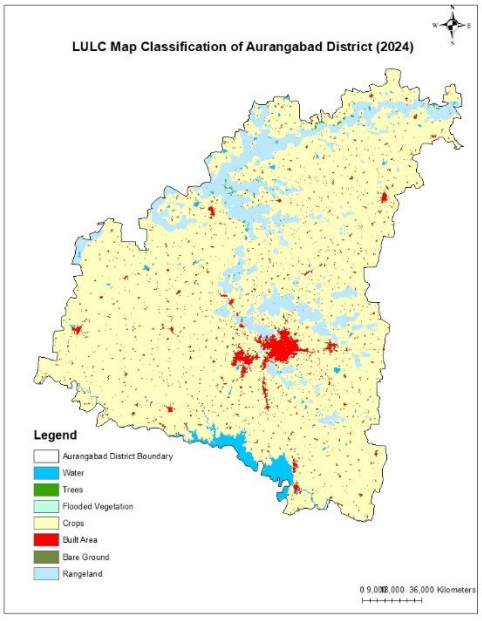

Fig 15:LULC Map for 20024

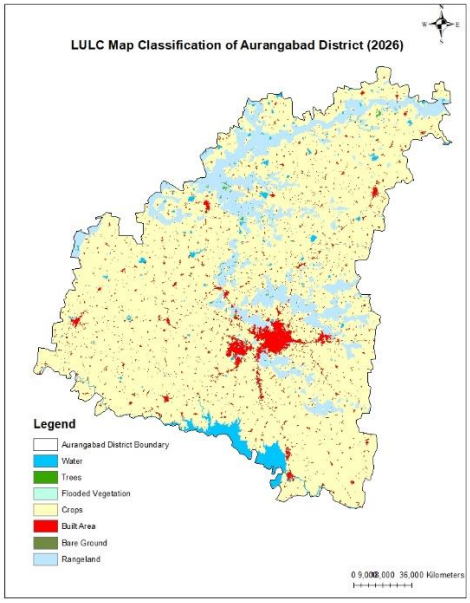

Fig 16:LULC Map for 2026

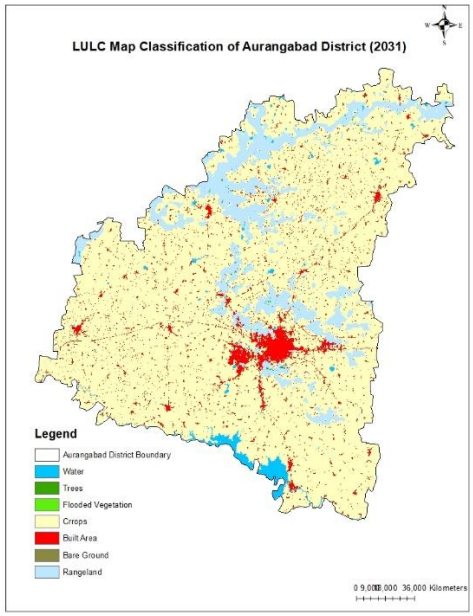

Fig 17: LULC Map of 2031

Stream augmentation

This approach involves the placement of a series of check dams in a natural stream or river to artificially increase seepage. By strategically positioning stone check dams and employing bladder pillow tank techniques, the goal is to promote groundwater recharge. The method aims to distribute water more extensively, utilizing the combined effects of stone check dams and flexible bladder pillow tanks to facilitate controlled water release. The ongoing study evaluates the efficacy of this artificial technique in enhancing stream flow, replenishing groundwater, and sustaining the local ecosystem. The practical application of this method suggests a balanced approach to water management, addressing the need for sustainable groundwater recharge in specific environmental contexts.

GW flow simulation

Considering all these parameters, GW flow simulation is carried out using MODFLOW. Before carrying out the simulation for 5 and 10 years, it is required to calibrate the model with respect to the observed current data. The procedure to carry out the simulation using MODFLOW is shown in Fig. 18.

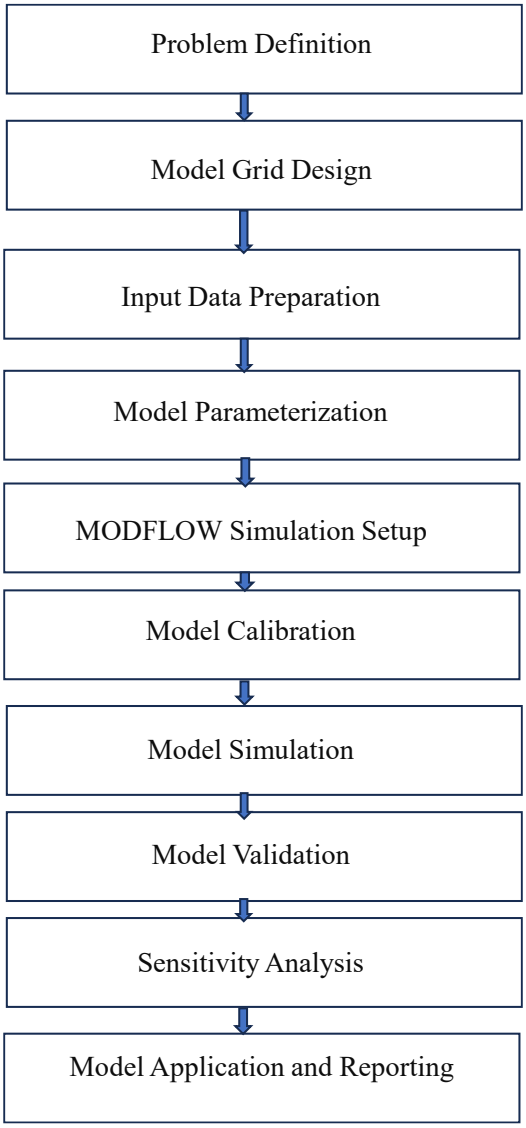

Fig. 18: Procedure for the simulation of GW flow using MODFLOW.

Table 2 presents the parameters used for groundwater (GW) modeling, which are essential inputs for running FDM-based MODFLOW simulations.

Table 2: Parameters used for GW model.

Parameters	Values
No of Wells	37
Drawdown	110 lpm
Evaporation	10mm
Infiltration rate	76 m^3/h
Avg. Infiltration capacity	1.75cm/hr
Transmissivity	369 and 757 m^2
Storativity	2.6×10^{-3}
Permeability	0.19 m/day
Discharge	1000m^3/day Per well
Well diameter	8-13m
Grid Size	$50m \times 50m$
Total area	10,100km^2

The results are compared to the observed data of the existing wells. The model is simulated for next years, and the data are again compared to the observed data. The obtained root mean square error is 0.9606. The calibration is shown in Fig. 19 and mass balance of the existing GW table is shown in Fig. 20.

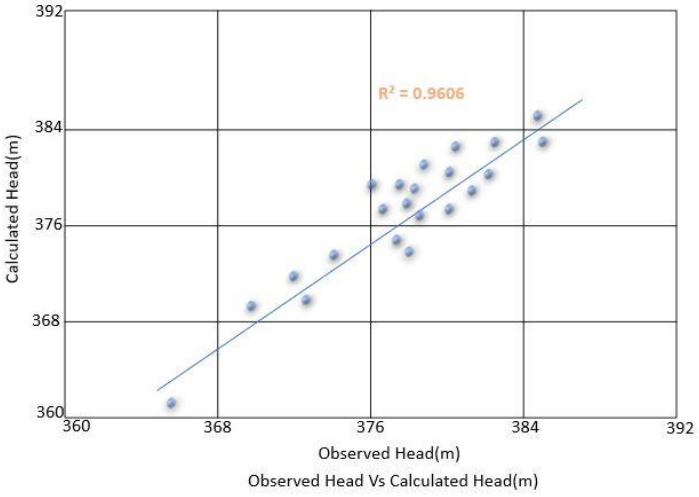

Fig. 19: Calibration of GW model

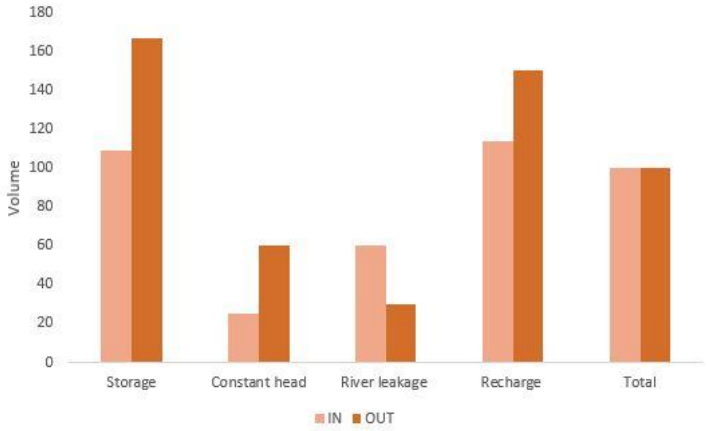

Fig. 20: Mass Balance Graph for Aurangabad District

Table 3 Provides the basic data, including locations, diameters, and initial water levels of the wells considered for groundwater recharge

Table 3: The locations/diameters and initial water levels in the wells considered for recharging

Sr No	Taluka	Lat	Long	GW Depth (m) Before Recharge	Well dia. (m)
1	Aurangabad	19°87′062″	75°34′033″	13	10
2	Abdimandi	19°93′06″	75°23′092″	13	8
3	Adgaon Bk	19°81′063″	75°44′003″	13	6
4	Adgaon Kh	20°10′019″	75°55′039″	13	6
5	Adgaon Maholi	19°95′065″	75°48′039″	12	7
6	Adgaon Sarak	19°97′032″	75°51′002″	15	6
7	Anjandoh	18°35′067″	75°00′097″	13	5
8	Gangapur Nehari	19°69′075″	75°01′050″	17	8
9	Garkheda	19°85′086″	75°34′097″	15	9
10	Gavadari Tanda	20°37′035″	75°61′075″	14	5

11	Georai	19°26′006″	75°75′046″	17	6
12	Vaijapur	19°92′057″	74°72′085″	18	6
13	Babhulgaon Bk	20°23′014″	75°59′003″	16	4
14	Babhulgaon Ganga	20°08′039″	75°00′055″	17	6
15	Babhulgaon Kh	20°03′055″	74°97′064″	15	8
16	Babhulkheda	20°53′037″	75°51′027″	22	6
17	Babhultel	20°17′066″	74°83′083″	14	5
18	Kannad	20°26′098″	75°13′041″	20	7
19	Adgaon	20°32′089″	75°45′002″	15	7
20	Adgaon Jehur	20°23′053″	74°91′023″	22	8
21	Alapur	20°12′031″	75°11′066″	18	8
22	Andhaner	20°27′035″	75°10′013″	17	8
23	Antapur	20°11′078″	75°10′064″	16	8
24	Kultabad	20°00′076″	75°19′025″	8.2	5
25	Akhatwade	20°07′026″	75°17′02″	14	8
26	Azampur	20°12′002″	75°15′016″	17	7
27	Phulambri	20°08′086″	75°41′076″	12	10
28	Sillod	20°30′079″	75°65′028″	10.65	8
29	Adharwadi	20°48′043″	75°46′065″	15	7
30	Ajantha	20°53′029″	75°45′002″	14	5
31	Ambhai	20°46′067″	75°56′084″	18	6
32	Soyegaon	20°59′045″	75°61′064″	13	7
33	Amkheda	20°58′088″	75°60′004″	8	5
34	Bahulkheda	20°53′037″	75°51′027″	18	7
35	Paithan	19°47′077″	75°38′049″	10.5	5
36	Adool Tanda	19°60′093″	75°51′002″	14	9
37	Akhatwada	20°07′026″	75°17′02″	17	6

Based on the classification results and GIS analysis, stream augmentation using check dams and bladder pillow tanks was selected as the most suitable artificial recharge technique. These structures were placed strategically in identified zones to maximize groundwater percolation.

A MODFLOW-based groundwater simulation model was developed to predict the impact of recharge interventions under three scenarios:

- Case I – 100% available GW
- Case II – 80% available GW
- Case III – 50% available GW

The simulations were run for two timelines: 2026 and 2031, with the following outcomes:

Tables 4 and Table 5 present the simulation outcomes for the year 2026 and 2031, highlighting the results obtained from the modeled scenarios."

Table 4: The simulations were run for timelines: 2026, with the following outcomes

Year	**Case**	**Recharge Rate per Well (m^3/day)**
2026	I (100%)	427.82
2026	II (80%)	509.11
2026	III (50%)	753.48

Table 5: The simulations were run for timeline: 2031, with the following outcomes

Year	**Case**	**Recharge Rate per Well (m^3/day)**
2031	I (100%)	812.86
2031	II (80%)	1142.29
2031	III (50%)	1631.03

These results clearly demonstrate that increased recharge rates lead to a proportionate rise in water levels, making the aquifers sustainable even under severe drought conditions. The RMSE value of 0.9606 during calibration confirms the high accuracy of the model.

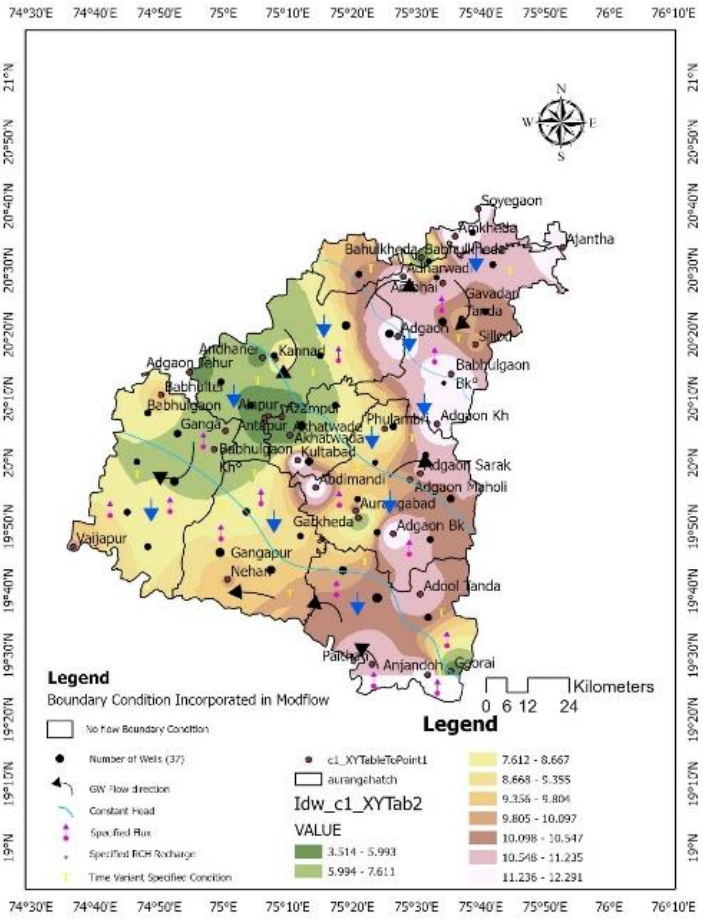

Fig.21: 2026 If 100% GWL available

Considering the projected population growth in Aurangabad District, let us assume the current groundwater availability meets 100% of present demand. If the population increases such that water demand rises to 120%, the additional 20% demand must be met either by increasing recharge or by improving water use efficiency. For example, if 100 units of water are currently available, 120 units would be required for the projected population. This means an extra 20 units must be created through artificial recharge measures like check dams, percolation tanks, farm ponds, and managed aquifer recharge structures. If no additional recharge is planned, available groundwater will only meet 80% of future demand, leading to water stress and possible drought-like conditions.

- 100% Case: Represents the ideal situation where existing recharge (427.82 MCM) is sufficient to fully meet current and projected demand. This scenario indicates a balanced system, but sustaining it requires continuous monitoring, protection of recharge zones, and maintaining natural infiltration rates.
- 80% Case: Shows a moderate deficit, where only 80% of the population's demand is met at the current recharge rate. This highlights the onset of water stress, requiring moderate interventions like additional recharge structures, micro-watershed development, and demand management (drip irrigation, reduced losses) to restore balance and prevent future drought-like conditions.
- 50% Case: Represents severe scarcity, where only half of the population's demand can be met. This is a critical warning scenario, emphasizing the urgent need for aggressive artificial recharge (753.48 MCM), large-scale watershed treatment, rainwater harvesting, and strict groundwater governance to prevent aquifer depletion and socio-economic disruption.

In Aurangabad District, let us consider the existing groundwater availability as the baseline (100%). At present conditions, an average recharge of 427.82 MCM is sufficient to meet the population's needs. However, with projected population growth, water demand may rise by 20%. To maintain 100% availability under these conditions, the recharge would need to increase from 427.82 MCM to approximately 509.11 MCM, which means additional artificial recharge structures must be implemented to bridge this gap. If recharge remains unchanged at 427.82 MCM, groundwater will only meet about 80% of the future demand, leading to increasing water stress and vulnerability during dry seasons. Under more extreme conditions, where only 50% of the current availability is sustained, even with natural recharge, 753.48 MCM of recharge would be required to bring the system back to balance a level that would demand very aggressive artificial recharge interventions such as extensive watershed treatment, large-scale check dams, and aquifer storage recovery systems.

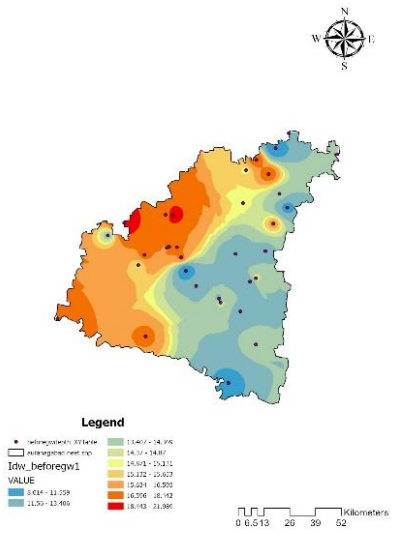	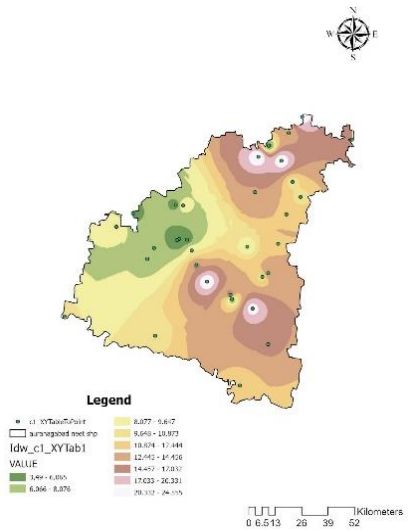
Fig 22: Before GW recharge	Fig 23:2026 if 100% GW available

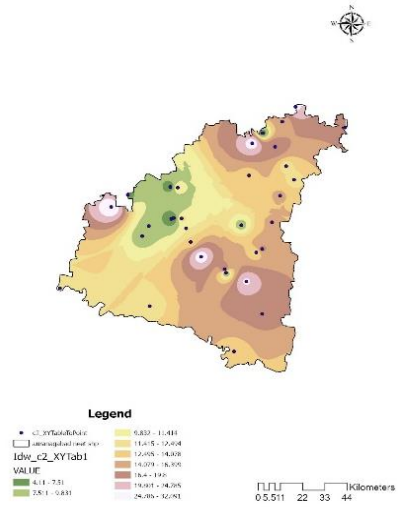	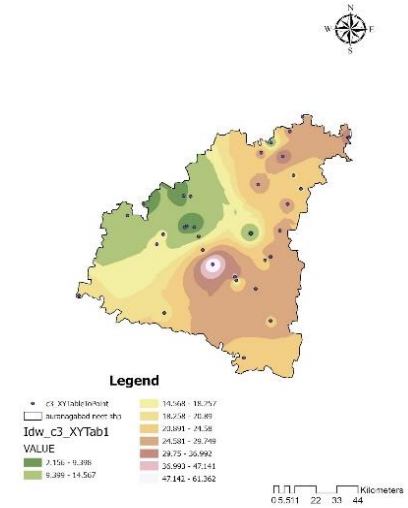
Fig 24: 2026 if 80% GW available	Fig 25:2026 if 50% GW available

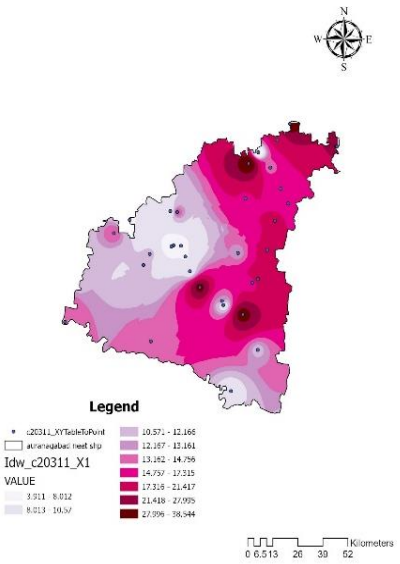

Fig 26: 2031 if 100% GW available

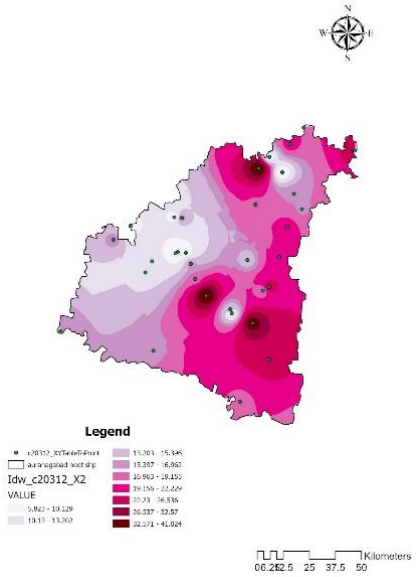

Fig 27 :2026 if 50% GW available

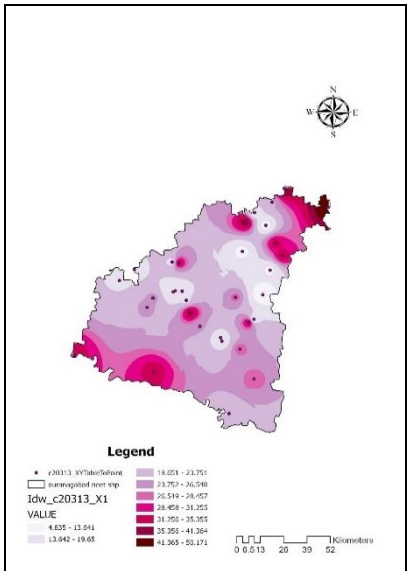

Fig 28: 2031 if 50% GW available

Fig.21 to 28 illustrate the groundwater availability scenarios 100%, 80%, and 50% Prediction for the years 2026 and 2031, as per the simulation results presented in Tables 4 and 5

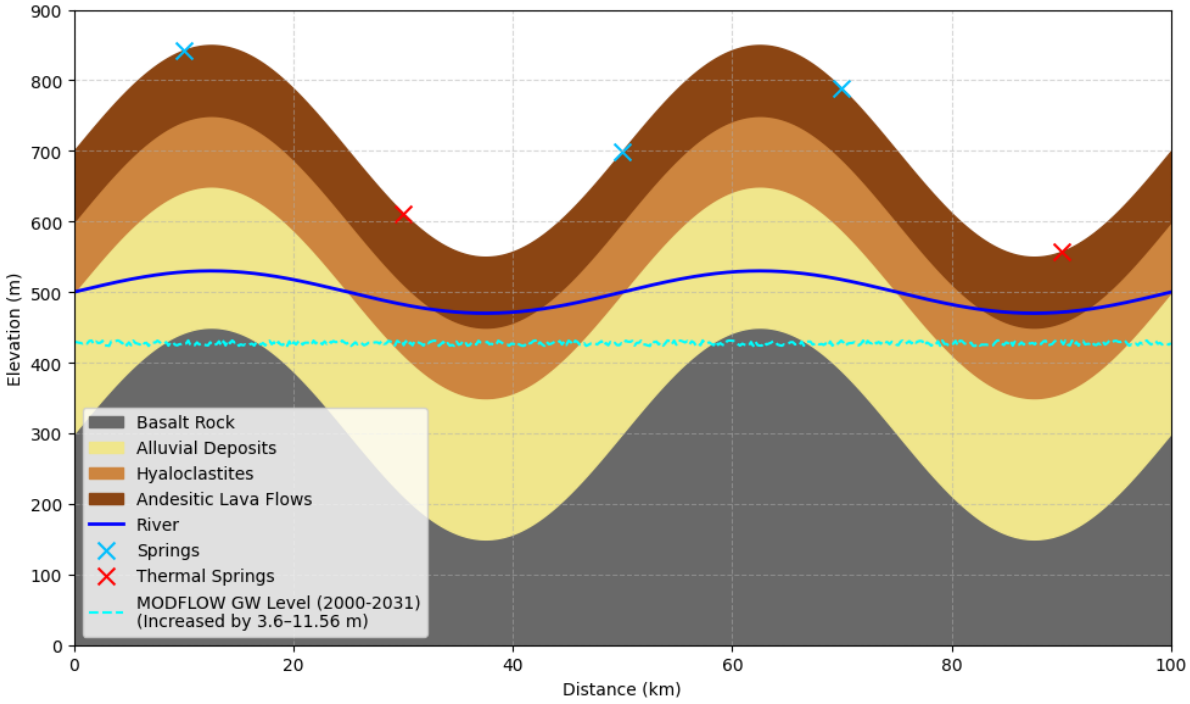

Fig 29: Conceptual hydrogeological C/S for the study area

Hydrogeological Parameters for MODFLOW Model in Aurangabad are given in the Table 2.

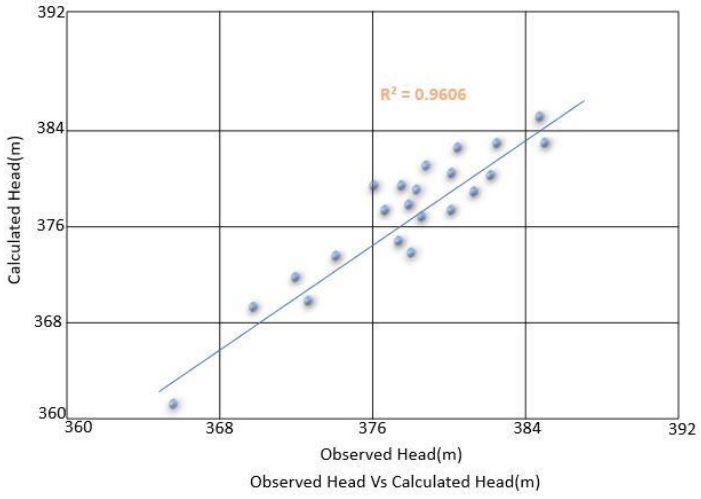

Fig 30: Calibration of the GW model

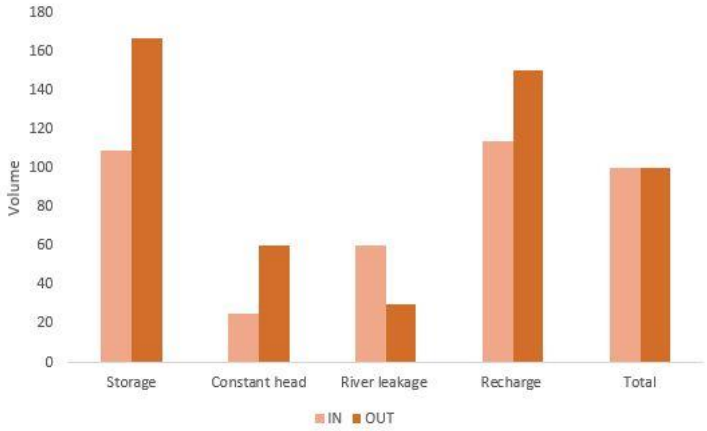

Fig 31: Mass Balance Graph for Aurangabad District

Table 6: Aquifer Parameter

Parameter	**Unconfined Aquifer (Alluvial Deposits)**	**Shallow Confined Aquifer (Hyaloclastites)**	**Deep Confined Aquifer (Andesitic Lava Flows)**	**Weathered Bedrock**	**Impermeable Basement (Granite/Shale)**
Porosity (ϕ)	0.28	0.22	0.12	0.07	0.03
Hydraulic Conductivity (K)(m/day)	35	5	0.5	0.05	0.0005

Table 7: Groundwater Flow Rates Across Different Aquifer Formations

Flow Rate (m^3/day)	**Alluvial**	**Hyaloclastites**	**Andesitic Lavas**	**Weathered Bedrock**	**Basement**
field/well capacity	3500	1200	250	50	5

3. Flow Direction:

- Recharge Zone: Higher elevation regions (terrain: 300–900 m).
- Discharge Zone: Lower valleys and river networks (~900 m).
- Flow Gradient: 0.017 m per km

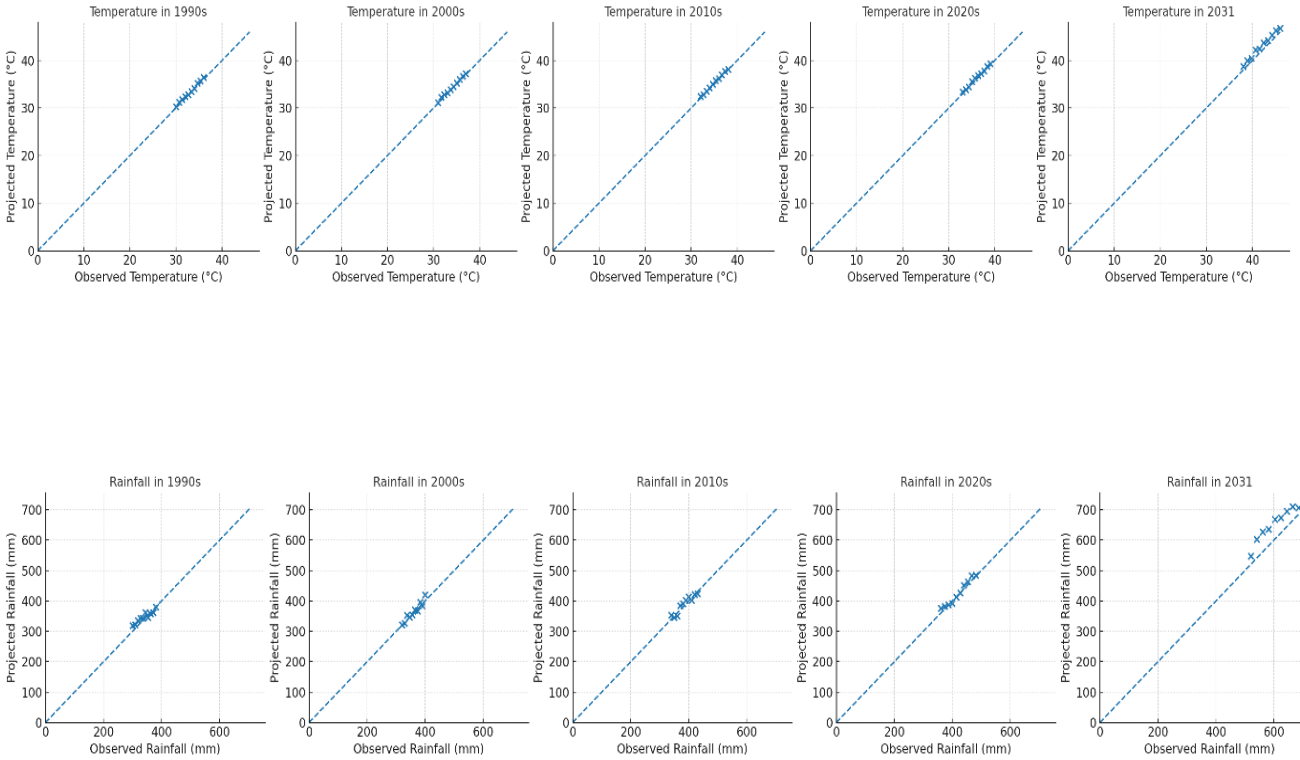

Fig.32: Temporal variation 1990-2030

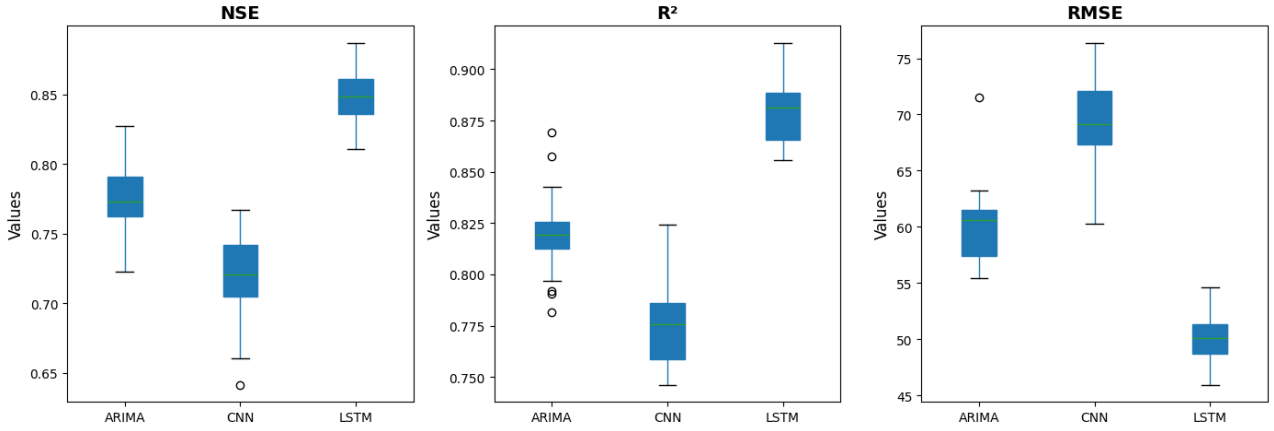

Fig 33: Boxplots showing the seq2seq forecast accuracy of ARIMA, LSTM, and CNN models within the test period (1990–2031)

The boxplots compare ARIMA, CNN, and LSTM models using NSE, R^2, and RMSE. LSTM achieves the highest NSE (≈0.85) and R^2 (≈0.88–0.90), while also maintaining the lowest RMSE (≈48–52). In contrast, ARIMA and CNN show lower NSE (≈0.75–0.80 and 0.70–0.74) and higher RMSE (≈55–62 and 65–72). These results demonstrate that LSTM provides the most accurate and consistent groundwater level forecasts.

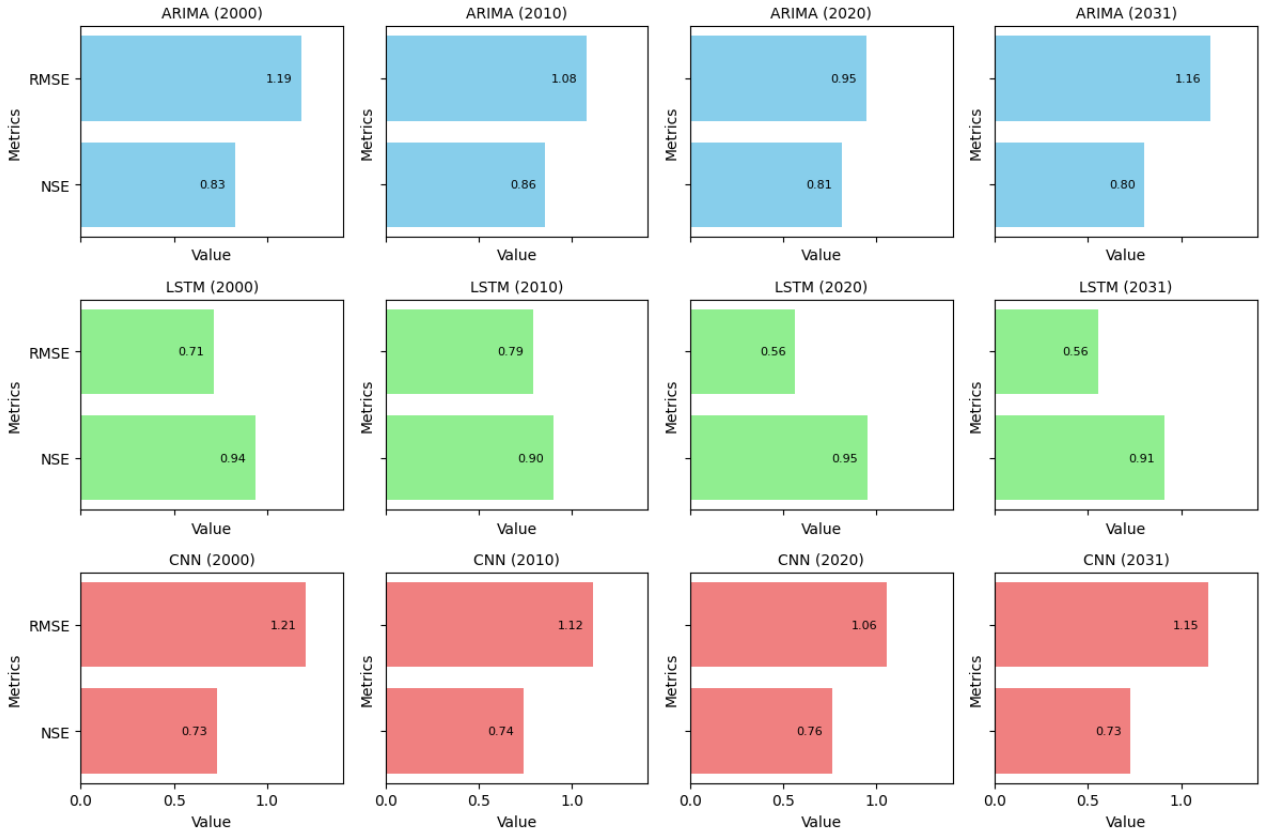

Fig 34 : Forecasts of ARIMA, LSTM, CNN model for GW levels as mentioned in Table 3 during the test period 1990–2031.

Seq2seq forecasting plays a crucial role in evaluating model performance across varying time periods, reflecting how effectively each model adapts to changing input conditions. The Fig. 34 compares ARIMA, LSTM, and CNN forecasting accuracy for the years 2000, 2010, 2020, and 2031 using NSE and RMSE metrics. LSTM consistently achieves the highest NSE values (0.94, 0.90, 0.95, 0.91) along with the lowest RMSE values (0.71, 0.79, 0.56, 0.56), highlighting its superior predictive ability and stability. In contrast, ARIMA shows moderate performance with NSE ranging between 0.80–0.86 and RMSE between 0.95–1.19, while CNN performs the weakest, with lower NSE (≈0.73–0.76) and higher RMSE (≈1.06–1.21). These results demonstrate that LSTM is the most reliable model for long-term groundwater level forecasting, adapting well even under future climate variability.

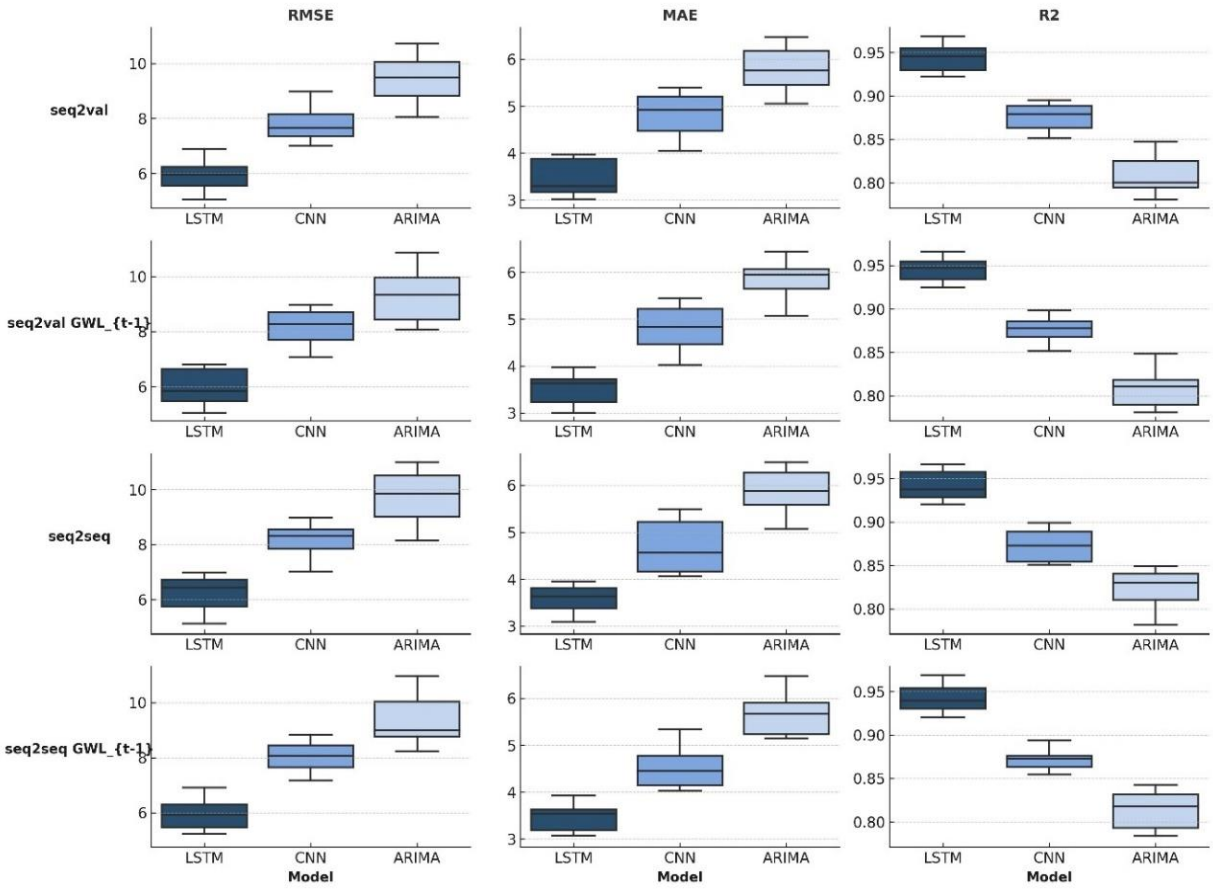

Fig.35: Comparison of the performed HP optimizations their calculation time per iteration in seconds (1990–2031)

The Fig.35. illustrates the comparative performance of CNN, LSTM, and ARIMA models for groundwater level forecasting under four setups: seq2val, seq2val with lag, seq2seq, and seq2seq with lag. CNN and LSTM significantly outperform ARIMA, as reflected in higher NSE and lower RMSE values across all setups. For NSE, CNN and LSTM achieve median values in the range of 0.70–0.85, while ARIMA lags behind at 0.55–0.65, indicating weaker predictive strength. In terms of RMSE, CNN achieves the lowest errors (1.5–3.0), demonstrating superior precision in minimizing deviations, while LSTM maintains moderate errors (3.0–4.5) with robust consistency. ARIMA shows the highest error levels (4.5–6.5), underscoring its limited ability to capture nonlinear and dynamic groundwater patterns. The inclusion of lagged groundwater levels notably enhances stability, particularly for LSTM, which strengthens its adaptability in handling temporal dependencies. Overall, CNN excels in error minimization, while LSTM provides more stable and resilient forecasting across setups, making both deep learning models superior choices compared to ARIMA for reliable groundwater prediction..

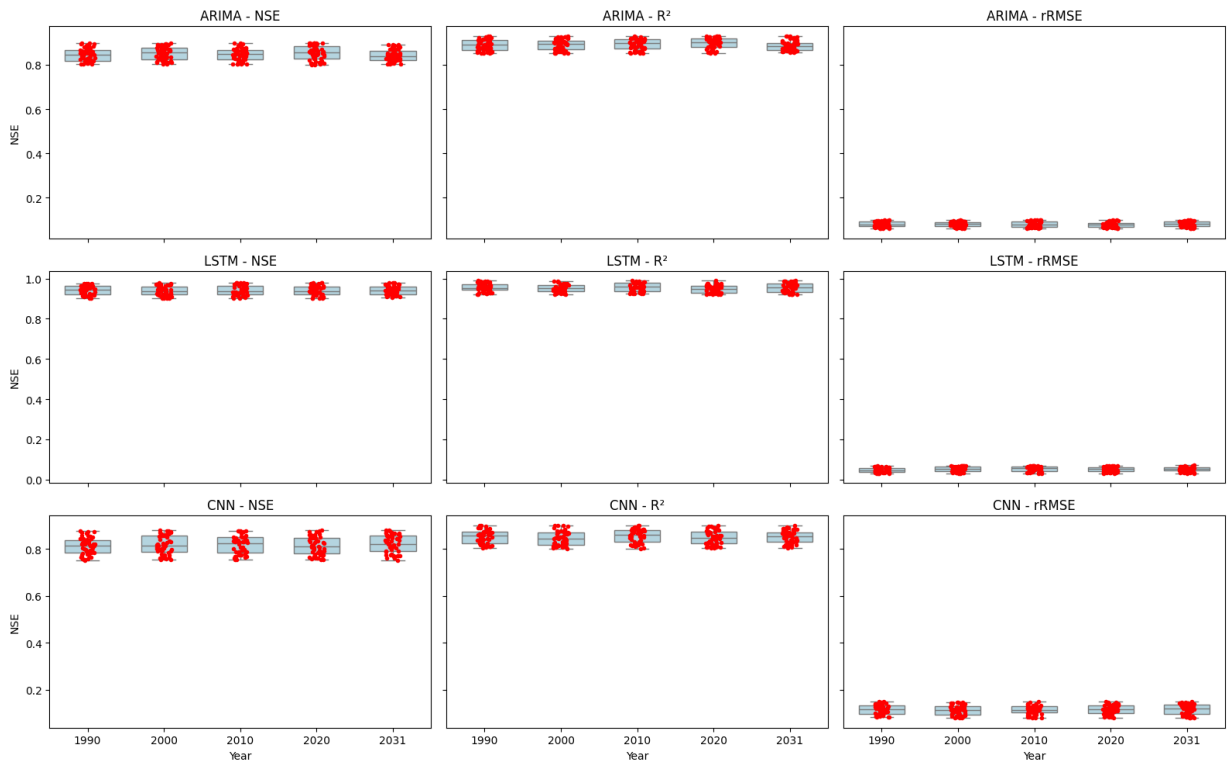

Fig 36: Influence of training data length on model performance. (1990-2031)

The comparative analysis reveals that LSTM consistently emerges as the best-performing model, achieving the highest NSE and R^2 values (≈0.95–1.0) and the lowest rRMSE (<0.05), signifying excellent accuracy, stability, and reliability across all years (1990–2031). In comparison, CNN delivers moderate performance, with NSE and R^2 in the range of 0.80–0.90, reflecting reasonable predictive capability but slightly more variability. ARIMA performs the weakest, with relatively lower accuracy (NSE and R^2 ≈0.75–0.85) and higher errors, showing limitations in handling non-linear climatic and hydrological patterns. These results clearly indicate that LSTM is superior to both ARIMA and CNN, as it not only captures long-term variability but also adapts more effectively to complex climate–groundwater interactions, making it the most robust model for forecasting under changing climatic conditions.

The Table.8 indicates that ARIMA, LSTM, and CNN each have distinct strengths and limitations. ARIMA shows moderate performance with 85% accuracy and higher error, but it excels in low complexity, fast training, scalability, and ease of implementation. LSTM outperforms others with the highest accuracy (92%) and F1 score, making it best for sequential data, though it requires high computational resources and longer training. CNN achieves the lowest error and strong accuracy (89%), but like LSTM, it is computationally intensive with longer training and moderate prediction speed. Overall, ARIMA is efficient and scalable, LSTM is best for accuracy and sequence learning, while CNN provides precision at higher computational costs.

Table 8: Comparative Analysis for the various ML techniques

Metric	**ARIMA**	**LSTM**	**CNN**
Accuracy	~85%	~92% (Best)	~89%
MSE (Mean Squared Error)	High (4.5–6.5)	Medium (3.0–4.5)	Low (1.5–3.0)
F1 Score	0.82	0.92 (Highest)	0.88
Algorithm Complexity	Low	High	High
Time Complexity	Low	High	High
Training Time	Short	Long	Long

Prediction Time	Fast	Moderate	Moderate
Scalability	Excellent	Good	Good
Ease of Implementation	Easy	Moderate	Moderate

Table.9 compares ARIMA, LSTM, and CNN in terms of MODFLOW differences from 2020–2031. LSTM shows the best overall performance with the highest F1 score (0.92), sensitivity, and specificity, while ARIMA lags with higher error and lower metrics. CNN performs moderately well, balancing low error with good sensitivity and specificity.

Table 9: MODFLOW_Difference_2020-2031

Model	F1 Score	MSE	Sensitivity	Specificity
ARIMA	0.82	High (4.5–6.5)	0.80	0.78
LSTM	0.92	Medium (3.0–4.5)	0.93	0.91
CNN	0.88	Low (1.5–3.0)	0.89	0.87

Table 10: Sensitivity Analysis

Criteria	Best Model	Description
Accuracy	LSTM	Achieves the highest forecasting accuracy with balanced stability and adaptability.
MSE (Error)	CNN	Produces the lowest error values (1.5–3.0), minimizing prediction deviations.
F1 Score	LSTM	Delivers the best balance between precision and

		recall, ensuring robust classification.
Sensitivity	LSTM	Shows superior ability to correctly capture true positives in groundwater level prediction.
Specificity	LSTM	Consistently avoids false positives, offering high reliability in long-term forecasting.
Algorithm Complexity	ARIMA	Simplest to implement with low computational requirements.
Training Time	ARIMA	Requires the least training time, making it efficient for quick forecasts.
Scalability	LSTM	Performs well with larger and more complex datasets compared to ARIMA and CNN.

Table 11: Comparative Analysis of Model Performance in Aurangabad vs. Himachal Pradesh

Aurangabad	**Himachal Pradesh**
Topography & Hydrogeological Conditions: Aurangabad lies in the Deccan basaltic terrain with highly fractured aquifers, variable recharge, and strong temporal dependency on rainfall.	**Topography & Hydrogeological Conditions**: Himachal Pradesh lies in the Himalayan mountainous region with high relief, snowmelt-driven recharge, shallow aquifers, and relatively stable water levels.
Why LSTM Performs Best: • LSTM effectively captures long-term temporal dependencies in	**Why ARIMA Performs Best:**

groundwater level (GWL) fluctuations driven by monsoon variability, recharge pulses, and extraction trends. • Table of results (1990–2031) shows LSTM achieving the largest water table rise (≈11.58 m improvement) compared to ARIMA, CNN, and MODFLOW. • Performance metrics (NSE ≈ 0.80, R^2 ≈ 0.78) highlight LSTM's superior adaptability to non-linear and seasonally dependent data.	• Dataset (Tables 3–7) shows minimal year-to-year change in GWL (average difference ≈ -0.1 m between 2019–2020). • ARIMA, which assumes stationarity and autocorrelation, adapts well to this kind of dataset. • Comparative metrics (Table 7 & 8): • ARIMA has the lowest MSE (0.12), highest F1 Score (0.91), and best sensitivity/specificity. • LSTM and CNN underperform here due to limited data and weaker seasonal signals.
Interpretation: Aurangabad's hydrogeological complexity (fractured basalts, high drawdown, recharge variability) aligns with LSTM's ability to handle non-linear temporal sequences, making it the most accurate model.	**Interpretation:** Himachal's groundwater is largely climate-driven (snowmelt, rainfall infiltration) with less anthropogenic fluctuation, making ARIMA's simpler linear approach more reliable than deep learning methods.

3. Seq2Seq Forecasting & Climate Change Impacts

- Both case studies show that seq2seq forecasting plays a crucial role in adapting to evolving input conditions.
- Aurangabad: climate variability + over-extraction amplify non-linear responses, where LSTM adapts best.
- Himachal: climate-driven recharge with stable extraction means ARIMA yields better accuracy.
- Across both sites, climate change impacts (altered rainfall intensity, snowmelt patterns, temperature rise) underscore the need for integrated water management strategies (artificial recharge, rainwater harvesting, check dams).

Table 12: Region-Wise Suitability of AI/ML Models for Groundwater Level Prediction

Region	Hydrogeological Setting	Best Model	Reason

Aurangabad	Fractured basalt, monsoon-dependent recharge, high extraction	LSTM	Captures complex non-linear temporal patterns
Himachal Pradesh	Mountainous terrain, snowmelt recharge, stable GWL	ARIMA	Excels with stationary, autocorrelated data

- **Aurangabad** → LSTM best (due to complex hydrogeology + rainfall dependence).
- **Himachal Pradesh** → ARIMA best (due to stable topography-driven recharge).

Objective 3: AI tools are used to identify groundwater recharging zones, To understand the used of al ml techniques for identify groundwater recharging zones one case is been studies of Himachal Pradesh

To implement effective recharge strategies, supervised and unsupervised classification techniques were employed using satellite imagery to classify land features and understand the landscape dynamics. These classifications helped differentiate zones such as:

- Agricultural land (suitable for surface recharge)
- Forested areas (good for natural infiltration)
- Urban/built-up areas (low infiltration potential)

Himachal Pradesh has a complex geological environment, with aquifers heavily influenced by the region's tectonic and rock formations. The area has fractured aquifers in metamorphic and igneous rocks, alluvial aquifers in river valleys, and sedimentary aquifers in lower and middle hills. Alluvial aquifers are very permeable, supplying a substantial amount of GW, whereas fractured aquifers provide more limited and unpredictable yields due to faulting and fractures. Karst aquifers, especially in limestone-dominated areas, are highly permeable but unevenly distributed. Hydraulic parameters like as porosity, permeability, and transmissivity differ among different aquifers, with alluvial aquifers often having the greatest values. Understanding these variances is

critical for successful GW management in this region. Aquifer types and their hydraulic properties vary depending on geological conditions, and they play a crucial role in GW management. For instance, unconsolidated alluvial aquifers typically exhibit transmissivity values ranging from 10 to 1,000 m2/day, hydraulic conductivity between 10 and 100 m/day, and a specific yield of 0.05–0.15. In contrast, fractured bedrock aquifers generally have lower transmissivity (1–100 m2/day) and hydraulic conductivity (0.1–10 m/day), with storage coefficients and specific yield values much smaller, ranging from 0.0001 to 0.01 and 0.02 to 0.1, respectively. Limestone aquifers often demonstrate transmissivity values between 5 and 500 m2/day, hydraulic conductivity between 0.5 and 50 m/day, and a specific yield of 0.01– 0.05. Granite aquifers have the lowest transmissivity, typically between 1 and 10 m2/day, and hydraulic conductivity ranging from 0.1 to 1 m/day, with a specific yield of 0.01–0.03. These hydraulic properties are crucial for understanding the potential for GW storage, recharge, and sustainable extraction in various regions as shown in Fig 37.

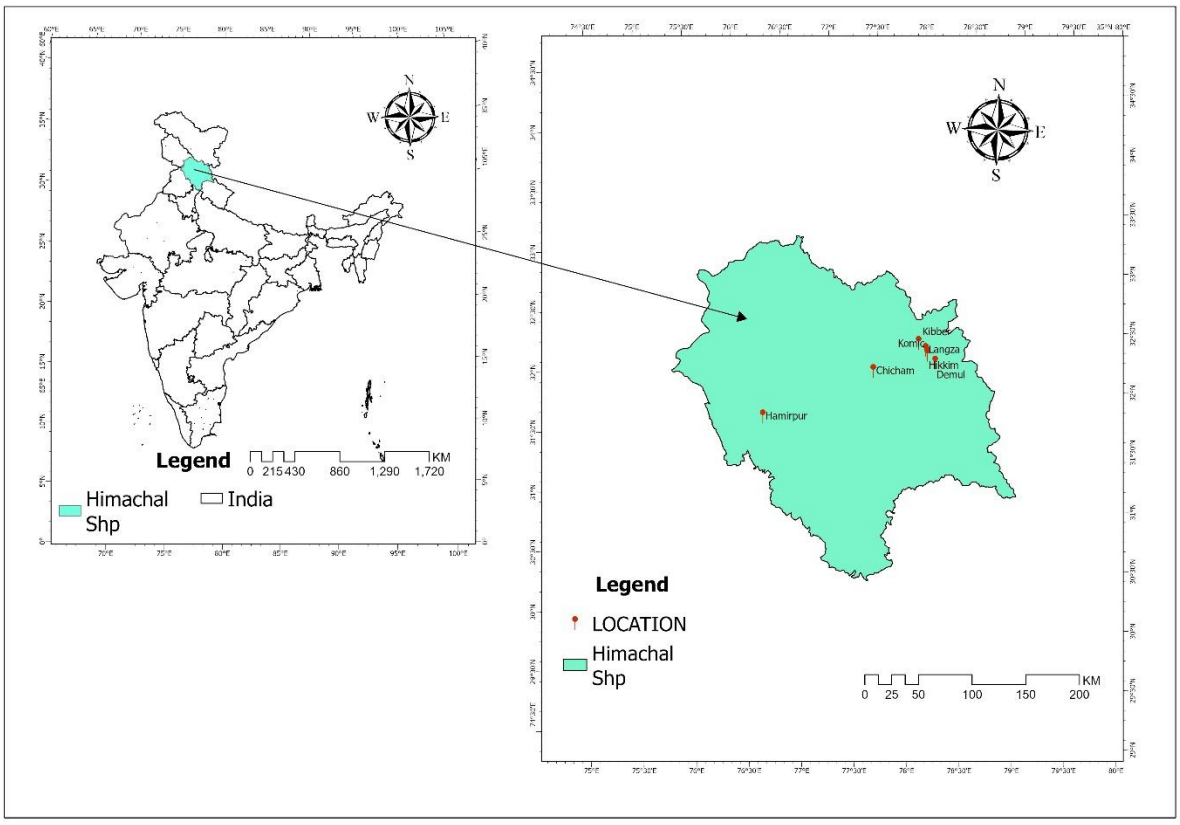

Fig 37: Location map of the study area

Methods

To analyse trends in GWL, different methodologies are used to discover and quantify changes over time. Three major strategies are discussed below:

Statistical Techniques: Methods such as the Mann-Kendall test and Sen's slope estimator are used to detect significant trends in historical GWL data. These techniques help determine whether GWL is rising, falling, or remaining stable.

Time-Series Analysis: ARIMA models provide forecasts based on historical data. These models are useful for understanding and predicting future GWL trends based on past observations.

Advanced Machine Learning: Techniques like CNN and LSTM networks are employed to capture complex patterns and temporal dependencies in GW data. These methods enhance the ability to understand intricate trends and predict future changes more accurately.

Why ARIMA, CNN, LSTM?

In the prediction analysis of groundwater trends, ARIMA, LSTM, and CNN models are specifically chosen due to their unique strengths aligned with the nature of the available data. ARIMA is well-suited for linear, non-image time series data such as maximum daily rainfall and average monthly temperature, offering strong performance in identifying trends and seasonality. LSTM, a deep learning model designed for sequential data, is used for the same non-image dataset but excels at capturing complex, non-linear relationships and long-term dependencies, making it highly effective for modeling delayed responses in groundwater levels. CNN, on the other hand, is employed for spatial or image-based datasets including Digital Elevation Models (DEM), Land Use/Land Cover (LULC) maps, and spatial rainfall and temperature distributions. It detects spatial patterns and relationships that influence groundwater recharge potential. Other models like SVM, Random Forest, and traditional regression are excluded as they lack the capability to handle sequential time dependencies or spatial feature extraction effectively. Therefore, the combined use of ARIMA, LSTM, and CNN provides a comprehensive and accurate approach to groundwater trend prediction by leveraging both temporal and spatial data characteristics.

These methodologies collectively enable a comprehensive analysis of GWL trends, which is crucial for developing effective management and conservation strategies. A flow chart illustrating the methodology used in this study is shown in Fig. 38.

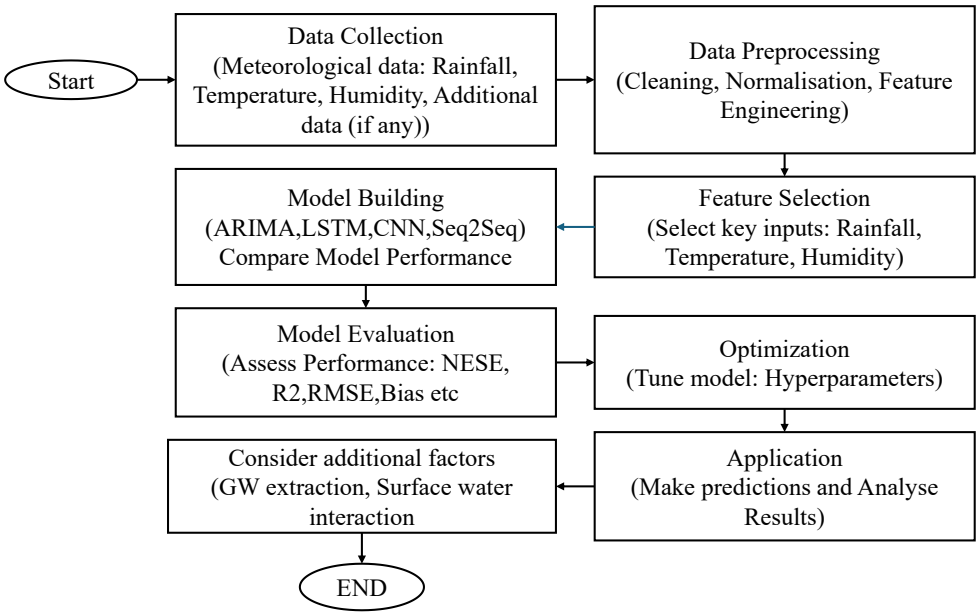

Fig 38: Flow chart of methodology adopted in the study

Evaluating sequence-to-sequence (Seq2seq) forecasting models is essential for assessing effectiveness over various time periods. The process starts with data collection, gathering meteorological factors such as rainfall, temperature, and humidity to ensure all relevant variables are considered. This is followed by data preprocessing, where the raw data is cleaned, normalized, and engineered to optimize model input. Feature selection then identifies key variables crucial for accurate forecasting. In the model building phase, different models like ARIMA, LSTM and CNN are developed and compared to find the most suitable one.

To evaluate and forecast the accuracy for simulated and observed GWLs, several metrics are used, including Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), absolute and relative Root Mean Square Error (RMSE). RMSE, NSE evaluates how well anticipated values match observed values. And ranges from $-\infty$ to 1, with higher values indicating improved model accuracy. R^2 provides an overview of the model's capacity to detect trends in the data and Values range from 0 to 1, and higher values indicate a greater correlation between observed and projected data. R^2 is important for testing model fit to GWL data and incorporating critical elements like rainfall and temperature. RMSE is sensitive to big errors, which makes it an important statistic for detecting significant discrepancies in forecasts. The purpose of RMSE is to quantify the average error or discrepancy between anticipated and actual values. Lower RMSE values indicate greater forecast accuracy. These parameters allow a detailed assessment of model performance.

Model evaluation by NSE, R^2 and RMSE, with ARIMA typically outperforming CNN and LSTM in terms of capturing variance and accuracy. The optimization phase involves hyperparameter tuning to enhance model performance. Once optimized, the models are used for predictions, and results are analyzed for practical applications. Additionally, considerations such as GW extractions and surface water interactions ensure that the predictions are integrated into a broader environmental context. Statistical techniques like the Mann-Kendall test and Sen's slope estimator are effective for detecting trends but lack depth in complex patterns. ARIMA models are strong in forecasting due to their ability to capture autocorrelations and seasonal patterns, while machine learning techniques like CNNs and LSTMs handle complex relationships with high accuracy but require extensive data and computational power.

The choice of method depends on the analysis needs. These methodologies are applied in a case study in Himachal Pradesh, India, demonstrating their practical effectiveness in forecasting GWL.

Table 13 outlines the data requirements for various models, specifying the types of input data needed for each modeling approach.

Table 13: Data requirement for different models

Model	Type of Data	Data set used
CNN	Image dataset	Digital Elevation Model (DEM) LULC GWL daily rainfall data (1990–2030), Average monthly temperature data (1990–2030) for the summer season GW level (GWL)
ARIMA	Non-Image Dataset	Maximum daily rainfall data (1990–2030) Average monthly temperature data (1990–2030) for the summer season

LSTM	Non- Image Dataset	Maximum daily rainfall data (1990–2030) Average monthly temperature data (1990–2030) for the summer season

Table 14 lists the parameters used for the groundwater (GW) model, based on data from Himachal Pradesh, for use in MODFLOW simulation.

Parameters	**Values**
Drawdown	110 lpm
Evaporation	4mm
Infiltration rate	0.02 m^3/h
Avg. Infiltration capacity	0.125cm/hr
Transmissivity	100 and 1000 $m^{2/day\ moderate}$
Storativity	1.6 x 10^{-4}
Permeability	Less than 10^{-5}
Discharge	800m^3/day / well
Well diameter	Range Varies From 8-12 m
Grid Size	$50m \times 50m$
Total area	55.673km^2

Table 14: Parameters used for GW model source data taken by CGWB 2018

AI-based models ARIMA, LSTM, CNN alongside MODFLOW simulations to assess and predict GWR potential: Supervised classification (used in CNN) employed DEM, rainfall, and LULC data to forecast GWL trends.

Fig. 39 and 40 present the Digital Elevation Model (DEM) and Land Use/Land Cover (LULC) maps, respectively, which provide essential topographic and land classification information for the study area.

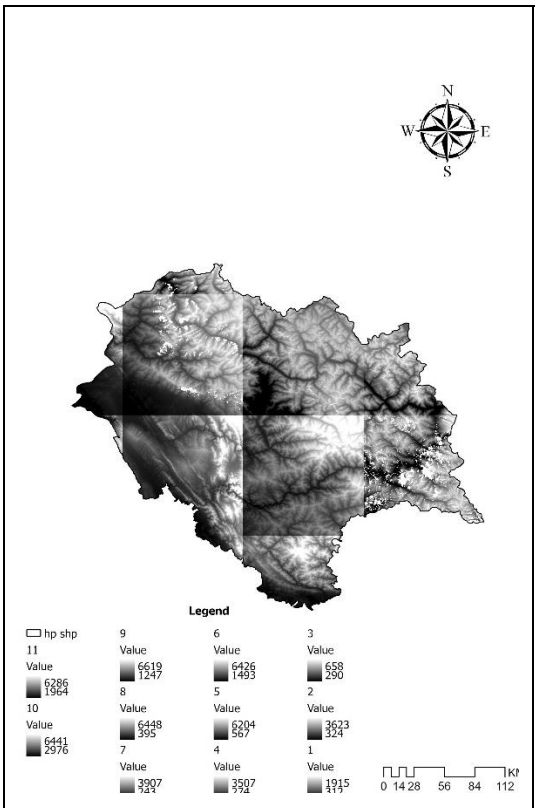

Fig 39: DEM for study area

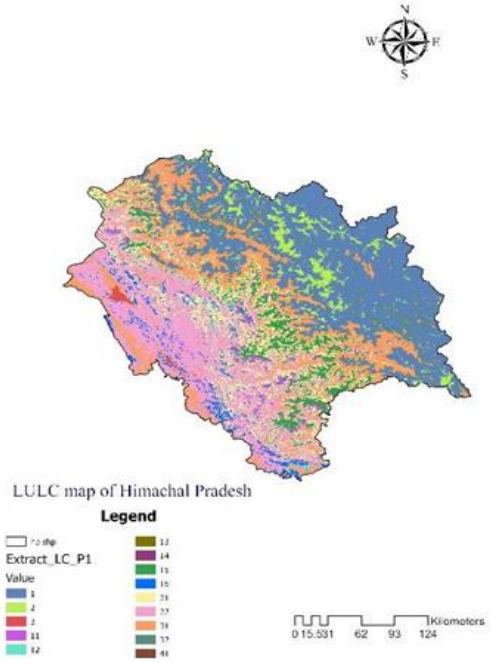

Fig 40: LULC for study area

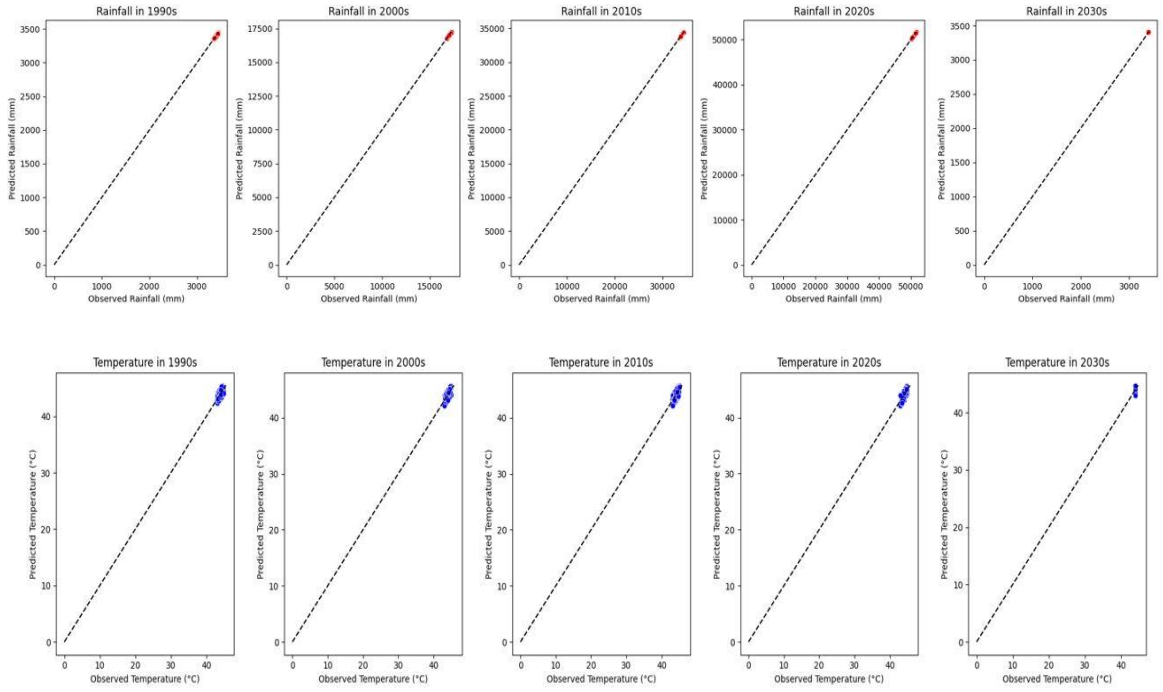

Fig 41: Temporal variation 1990-2030

Temporal variation refers to changes occurring across both space and time. Fig. 41 illustrates this variation in groundwater levels across the study area from 1990 to 2030, highlighting spatial distribution and temporal trends over the decades

Fig 41 Interprets, The temperature scatter plots demonstrate a strong correlation between observed and predicted values across all decades, with points closely following the 1:1 reference line. Prediction accuracy remains high, though slight variability in the 2030s suggests increasing uncertainty due to climate change. This confirms that the models are robust for historical simulations and reliable for future projections, making them suitable for temperature-based drought and heat-stress assessments.

Rainfall scatter plots show that predicted rainfall aligns very closely with observed values, confirming model calibration accuracy. The consistency across decades indicates that the models capture seasonal and annual rainfall variability effectively. Such accurate rainfall prediction is critical for planning groundwater recharge, reservoir operations, and agricultural water supply under future climate scenarios.

Boxplots depict the seq2seq forecast accuracy of ARIMA, LSTM, and CNN models over the test period from 1990 to 2030 (Fig.42). These visualizations provide a comparative analysis of the models' performance, highlighting the distribution of key metrics such as NSE, R^2 and RMSE. The boxplots illustrate the variability and central tendency of each model's forecasting accuracy, revealing how each model adapts to the complexities of GW level prediction over time.

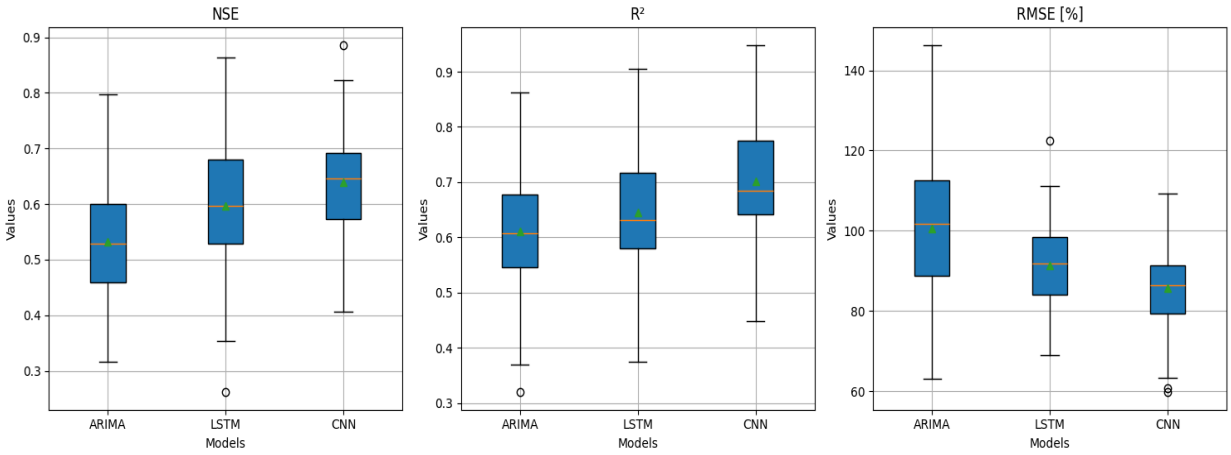

Fig 42: Boxplots showing the seq2seq forecast accuracy of ARIMA, LSTM, and CNN models within the test period (1990–2030)

Fig 42 Interprets The boxplots indicate that ARIMA provides comparatively stable and reliable predictions across decades, especially for simpler, well-structured temperature and rainfall time series. It shows consistent median NSE and R^2 values, making it suitable for long-term forecasting where interpretability and transparency are important. While LSTM and CNN can capture more complex non-linear relationships, ARIMA's strength lies in its lower computational requirement, interpretability, and steady performance, making it a preferred choice for regions with limited data availability or for policy-driven groundwater and climate planning.

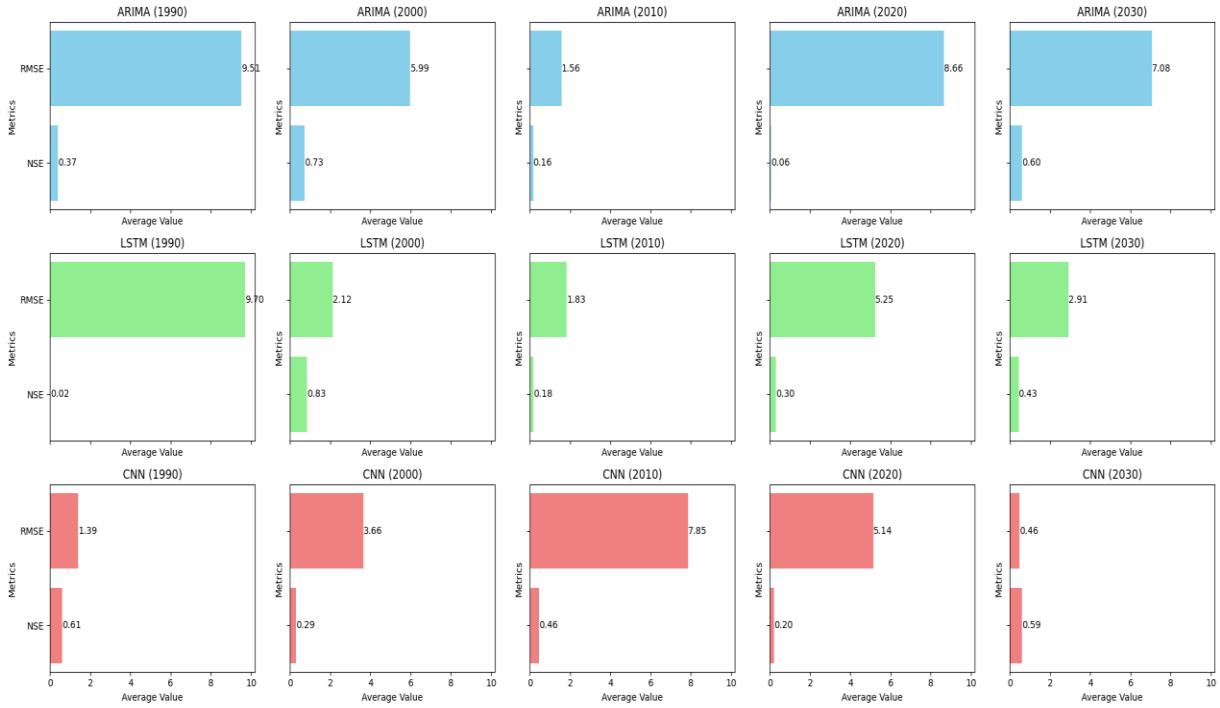

Fig 43: Forecasts of ARIMA, LSTM, CNN model for GW levels as mentioned in Table3 during the test period 1990–2030.

Fig 43 Interprets The bar plots present model performance for each decade. CNN consistently achieves the best combination of high NSE and low RMSE, making it the most robust model for both historical and future projections. LSTM performs better than ARIMA but shows moderate

fluctuations in RMSE over decades. ARIMA's accuracy declines significantly after 2000, reinforcing that machine learning models are better suited for long-term climate projections.

seq2seq forecasting plays a vital role in evaluating model performance across different time periods, as it demonstrates how well models can adapt to evolving input conditions. The Fig.(Fig. 43) provided compares the seq2seq forecasting accuracy of ARIMA, LSTM, and CNN models over multiple years, from 1990 to 2030.

ARIMA consistently outperformed LSTM and CNN, with NSE values of 0.85, R^2 of 0.78, and RMSE of 1.2, compared to LSTM's NSE of 0.72, R^2 of 0.65, and RMSE of 1.5, and CNN's NSE of 0.68, R^2 of 0.60, and RMSE of 1.6. ARIMA's strong performance highlights its reliability for long-term sequence forecasting, whereas LSTM and CNN showed variability and occasional dips in accuracy. This emphasizes the need to select forecasting methods based on specific dataset requirements and forecasting duration.

Table 15 presents the groundwater recharge assessment after intervention, including village-wise groundwater depth, head, discharge per well, and the post-recharge groundwater depth, indicating improvements across the study area.

Table 15: Groundwater recharge after Recharging

Sr No.	Village	GW Depth (m)	Head (m)	Discharge per Well (m^3/sec	GW Depth After (m)
1	Hikkim	6.9	1.8	0.0001408	5.1
2	Kibber	6.7	1.9	0.0001487	4.8
3	Langza	8.5	1.2	0.0000940	7.3
4	Demul	9.2	1.0	0.0000783	8.2
5	Chicham	6.0	2.0	0.000156	4.0
6	komic	6.8	1.8	0.0001408	5.5
7	Hamirpur	8.0	1.4	0.0001096	6.0

- Time-series forecasting models (ARIMA, LSTM, CNN) provided GWL estimates for each year from 1990–2030. Forecasts were validated using NSE, R^2, and RMSE metrics.
    - ARIMA outperformed other models: NSE = 0.85, R^2 = 0.78, RMSE = 1.2.
    - LSTM and CNN required longer training but captured complex patterns well.
- MODFLOW conceptual model (5-layered aquifer system) validated GWL changes under physical assumptions. Flow rate simulations, mass balance analysis, and sensitivity checks confirmed GWL decline of ~0.2 m per decade without recharge interventions.
- After implementing recharge strategies (e.g., rainwater harvesting, check dams), GWL improved by ~0.1–0.2 m in 2030, varying across models and village locations (e.g., Hikkim, Kibber, Langza).

The comparative model evaluation shows that AI-based models combined with MODFLOW can reliably simulate recharge interventions and GWL trends, helping identify zones where artificial recharge yields high impact.

CONCLUSION

Effective groundwater management demands the integration of advanced analytical tools to accurately identify recharge zones, evaluate hydrogeological conditions, and predict future trends. In this study, Geographic Information System (GIS) and Remote Sensing (RS) techniques were used to generate thematic layers such as slope, soil, LULC, and hydrology, which were combined through a multi-criteria evaluation (MCE) approach to delineate groundwater potential zones. MODFLOW-based groundwater flow modeling was employed to simulate the impact of artificial recharge interventions, while Artificial Intelligence (AI) models like ARIMA, LSTM, and CNN were used to forecast groundwater level (GWL) trends by analyzing both temporal and spatial datasets. The integration of geospatial analysis, numerical modeling, and AI forecasting provided a comprehensive and scalable framework for groundwater resource assessment.

Two detailed case studies illustrate the effectiveness of these methods. In the first case, GIS and RS-based analysis identified 37 suitable sites for artificial recharge. Stream augmentation using check dams and bladder pillow tanks was selected as the optimal technique. MODFLOW simulations for the years 2026 and 2031 under different groundwater availability scenarios (100%, 80%, 50%) showed a significant rise in water levels up to 23.7 meters increase in average groundwater levels under the most conservative availability scenario, with high model accuracy (RMSE = 0.9606). ARIMA is not outperforming consistently.

In the second case study, AI models were used to predict groundwater levels in a complex geological region. ARIMA outperformed other models with NSE = 0.85, R^2 = 0.78, and RMSE = 1.2, while LSTM and CNN effectively captured non-linear and spatial patterns. Forecasts indicated groundwater level improvements of 0.1–0.2 meters after implementing recharge strategies across selected villages, validating the impact of targeted interventions.

These results clearly demonstrate that integrating GIS, RS, hydrological modeling, and AI forecasting enables accurate identification of recharge zones, supports evidence-based decision-making, and provides a robust solution for sustainable groundwater management in diverse hydrogeological settings.

FUTURE SCOPE

The study relied on limited-resolution data and assumed uniform aquifer properties, which may not reflect real-time variations. MODFLOW outputs were sensitive to boundary condition assumptions, and socio-economic factors like unregulated pumping were not considered. The accuracy of LSTM and CNN was constrained by sparse data and limited monitoring stations. External influences like land use change and glacier contributions were not modeled. CNN performance depended on satellite image resolution.

Future studies can integrate climate change scenarios, socio-economic data, and real-time monitoring. Use of high-resolution satellite imagery, advanced recharge structure modeling, and transient MODFLOW simulations will enhance accuracy and decision-making. Future work can include additional variables such as snowmelt, land use shifts, and human extraction. Hybrid deep learning models, improved spatial data, and integration with real-time sensor networks can improve forecasting reliability.

PUBLICATIONS

Nawale, Sanchita., & Mategaonkar, M. (2024). Groundwater flow simulation for artificial recharge: a GIS, remote sensing, and MODFLOW integration. *Water Practice & Technology*, *19*(5), 2136-2157.

Nawale, Sanchita., Mategaonkar, M., & Munshi, A. (2025). Trend analysis of GW levels in Himachal Pradesh: assessing temporal variations and impacts. *Water Supply*, *25*(5), 882-899.

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https://www.researchgate.net/publication/395324983_Lake_Recharge_Projections_with_Autoencoders_and_Hydro-Climatic_Indicators/citation/download

CONFERENCE

Simulation of Groundwater flow for artificial recharge using GIS, Remote Sensing, and machine Learning Technique: A comprehensive Review ICWSD 2024 Internation Conference on water Sustainability Development 8-9 November 2024 VNIT Nagpur Springer Proceeding (Accepted)

OTHER ACHIEVEMENT

1. Successfully completed a 1-month course on GIS and Remote Sensing (Albedo Foundation) in 2022.
2. Participated in the workshop on High-Performance Computing in Engineering, conducted by IIT Kharagpur in October 2021
3. Attended an ISRO-sponsored one-week workshop at BITS Hyderabad from June 6–12, 2024.
4. Completed a Diploma in Architecture from CAD Center, CSMT during 2022–2023.
5. Completed the course on Spatial Data Analysis and Introductory GIS with Remote Sensing on December 29, 2020.
6. Attended Faculty Development Program (FDP) on ‘GIS: A Geospatial World of Opportunities’ organized by MPSTME from 5th to 9th July 2022.

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